Norwegian School of Economics Bergen, Spring 2022

# The role of M&A in managing emission risk

Do acquirers use M&A to improve their emission risk, and how does emission risk affect equity performance?

## Johannes Nordlie & Harald Aleksander Bjerke Christensson

Supervisor: José Albuquerque de Sousa

Master thesis, Economics and Business Administration Major: Financial Economics

## NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

## Acknowledgment

This thesis is written as a part of our master's degree in Economics and Business Administration and concludes our study at the Norwegian School of Economics. Writing this thesis has been a long and exciting process with both up and downs, but most importantly, it has been a great learning experience. We want to extend our sincere thankfulness to our supervisor José Albuquerque de Sousa, for his help along the way. His guidance, assistance, and encouragement while writing this thesis have been invaluable. Finally, we would like to thank each other, our family, and friends for their support.

Norwegian School of Economics

Bergen, June 2022

Johannes Nordlie

Harald Aleksander Bjerke Christensson

## Abstract

We study if companies use, or can use, M&A to reduce their emission risk and how this affects their short and long-term returns accounting for the materiality of emission-related issues. Our findings suggest that acquirers, on average, see an increase in emission risk resulting from the M&A. This indicates that firms are not actively using M&A to reduce their emission risk. However, we find a positive correlation between the target's emission score and the change in the acquirer's emission score. This finding implicates that firms can use M&A to reduce their emission risk if they incorporate an environmental aspect when evaluating the transaction.

When only evaluating transactions performed after the Paris agreement in 2015, we find weak evidence that reducing emission risk positively affects the acquirer's long-term returns. This contrasts our initial result when evaluating all transactions, as we then find no relationship between a changing emission risk resulting from the M&A and returns. The result can suggest that investor awareness related to emission risk changed after the Paris agreement as the risk of future environmental regulations and punitive actions increased.

## **Table of Contents**

1.	INTI	RODUCTION	.6
2.	LITI	ERATURE REVIEW	.9
_	2.1 2.2	M&A, ESG AND VALUE CREATION ESG, RISK, AND EQUITY PERFORMANCE	
3.	RES	EARCH QUESTIONS1	14
	3.1 3.2	<b>Hypothesis 1a)</b> Firms use M&As to improve their emission risk <b>Hypothesis 1b)</b> The change in acquirers emission score is positively correlated with the	
	3.3 3.4	RELATIVE DIFFERENCE IN EMISSION SCORE BETWEEN THE TARGET AND THE ACQUIRER	4L 15 4L
4.	DAT	A PROVIDERS AND SAMPLE SELECTION	17
4	4.1 4.1.1 4.2 4.3	CHOICE OF ESG RATING PROVIDER <i>Refinitiv emission score</i> INTRODUCTION TO SASB SAMPLE SELECTION	<i>17</i> 19
5.	MET	THODOLOGY	22
55555	5.1 5.2 5.3 5.4 5.5 5.6 5.7 5.7.1	MAPPING OF MATERIALITY	22 27 29 30 31 32
6.	RES	ULTS	34
6	5.1 5.2 5.3 5.4	Hypothesis 1a) Firms use M&As to improve their emission risk	36 <i>AL</i> 41
7.	ROB	BUSTNESS	46
	7.1 7.2	RESULT OF INSTRUMENTAL VARIABLE	
8.	LIM	ITATIONS AND FURTHER RESEARCH	51
8	8.1 8.2	LIMITATIONS FURTHER RESEARCH	52
9.			
10.		ERENCES	
11.	APP	ENDIX	52

## List of tables

Table 1 - Sample creation and criteria	20
Table 2 - Deals summarized by SDC macro industry	20
Table 3 - Deals by year of announcement	21
Table 4 - Summary statistics	21
Table 5 - The development in emission score of our treatment and control firms	25
Table 6 - Descriptive Statistics - Covariates Before and After Matching	27
Table 7 - IV: F-Test	33
Table 8 - OLS analysis of M&As effect on emission scores	39
Table 9 - Difference-in-difference analysis of M&As effect on emission scores.	40
Table 10 - OLS regressions measuring the effect of a change in emission score on acquire	irer
returns	43
Table 11 - Difference-in-difference regressions, measuring the effect of a change in	
emission score on acquirer returns.	44
Table 12 - Quadruple difference-in-difference	45
Table 13 - Instrumental Variable Regression	47
Table 14 - OLS measuring the impact of a change in emissions score on long-term returned	rns
only using transactions after the Paris agreement	50
Table 15 - Definition and explanations of terms and variables	62
Table 16 - Overview of industries used by SASB and coherent materiality score	63
Table 17 - Overview of the country or regional Fama-French factors used	64
Table 18 - SASB definition of materiality	65
Table 19 - VIF Test for Multicollinearity	65
Table 20 - Breusch-Pagan Test for Heteroskedasticity	66
Table 21 - Quadruple difference-in-difference with all interaction terms	67

## 1. Introduction

With new governmental policies making it more costly to pollute and investors starting to shy away from high-polluting companies, firms are investing in reducing their emission risk. Using Refinitiv's "Emission score" as a proxy for emission risk, this paper will look at how companies utilize mergers and acquisitions (M&A) to reduce this risk and internalize the cost of environmental externalities.<sup>1</sup> We examine how M&A changes the acquirer's emission risk and affects their subsequent short and long-term returns. We further investigate how the materiality of issues related to greenhouse gas (GHG) emissions in different industries affects acquirers' performance.

Several significant events have highlighted the changes in governmental policies and investor behaviors. The Kyoto Protocol, adopted in 1997 and put into force in 2005, was the first addition to the United Nations Framework Convention on Climate Change (UNFCCC) and the first legally binding treaty to reduce GHG. This treaty laid the foundation for the future significant climate agreement, most notably the Paris agreement of 2015, where 193 countries committed to keeping global warming to well below 2°C (United Nations, 2015). After the Paris agreement, banks and credit agencies began incorporating carbon risk through increased spreads and credit ratings (Delis et al., 2019; Seltzer et al., 2020). Moreover, these significant events, coupled with an increased focus by the population, media, and local governments, have made investors warier of climate change.

We also see new and stricter environmental regulations targeted toward companies. The European Commission is adopting the Corporate Sustainability Reporting Directive in April 2021, requiring firms to increase their environmental sustainability disclosure (European Commission 2021). Moreover, banks and financial markets will use sustainability-related key performance indicators to ensure firms comply with the upcoming EU taxonomy. These changes can pose rapid and significant challenges to firms, and for many, M&A can be a way to comply.

Institutional investors are now paying closer attention to companies' GHG emissions, and some have formed coalitions to collaborate with firms to reduce their carbon emissions (Bolton & Kacperczyk, 2021). Additionally, asset managers pressure companies to comply and adapt

<sup>&</sup>lt;sup>1</sup> We use the terms emission score, emission risk, environmental risk, and environmental profile interchangeably throughout this paper. Emission score refers to the score given by Refinitiv, while emission risk, environmental risk, and environmental profile represent what the emission score proxies.

to the new climate change policies. The world's largest asset manager, BlackRock, has committed to the net-zero 2050 ambitions and has raised the prospect of selling its shares in companies that do not comply (Mackenzie Michael & Nauman Billy, 2021). Harvard's endowment took it one step further and committed to selling all of its fossil fuel holdings (Kerber Ross, 2021).

To explore how firms can use M&A to meet the increasing regulations and disclosure requirements, we gather transactions where the acquirer has an emission score using the Refintiv database. This results in 797 unique firms and 1,169 completed transactions between 01.01.2002 and 01.06.2021. Based on these transactions, we employ multiple regressions using different techniques to explore how M&A affects acquirers' emission risk and their short and long-term returns.

Our findings suggest that firms generally do not use M&A to reduce their environmental risk. The difference-in-difference estimators with different control groups find that firms that perform an M&A see a statistically significantly lower emission score than non-M&A firms. This result suggests that most transactions are motivated by financial and operational synergies rather than improving their environmental risk. We argue that the lack of environmental aspects and complexity of integrating a new firm leads to this deterioration in emission risk. However, when redoing our OLS and difference-in-difference estimators using the relative difference in emission score as continuous treatment, we find the change in acquirers' emission score to be positively correlated with the relative emission score. <sup>2</sup> This indicates that firms who incorporate an environmental aspect in the decision-making can use M&A effectively to reduce their environmental risk.

Moreover, we are able to establish a weak relationship between reducing emission risk and long-term returns when only evaluating transactions performed after the Paris agreement in 2015. This finding can suggest that as the risk of future environmental regulations and punitive actions has increased, investors have become more environmentally aware and started to look more favorably at firms with lower environmental risks. However, we cannot establish a link between a reduced emission risk and short or long-term returns when utilizing our full sample

<sup>&</sup>lt;sup>2</sup> The relative difference in emission score is defines as:  $\frac{Target \ emission \ score}{Acquirer \ emission \ score} - 1$ 

of transactions, even when accounting for materiality. The latter result is consistent through our OLS and difference-in-differences. Without drawing any conclusion, we attribute the lack of results to the conflicting literature on how environmental investments affect returns

Our thesis contributes to the study on M&A's role in managing emission risk and how this affects their returns. The findings can help managers and corporations understand how they can use M&A to comply with new and future environmental regulations. To the best of our knowledge, a thesis has not been written that examines the effect M&As have on managing emission risk and how this relates to the acquirer's short and long-term returns when accounting for the industry materiality of GHG emission-related issues.

While Barros and Verga Matos et al. (2021) and Tampakoudis and Anagnostopoulou (2020) explored how M&A affects a firm's environmental, social, and governance (ESG) performance, we are being more granular, only looking at the emission score, a single pillar of the E in ESG. Bolton and Kacperczyk (2021) did examine if investors care about the risks associated with carbon emissions and found a statistically significant carbon premium. However, they did so through US stock returns. At the same time, we look for evidence through M&A. Khan et al. (2016) researched how a firm's sustainability affects equity returns and took it one step further by including the Sustainability Accounting Standards Board (SASB) materiality map in combination with the KLD sustainability score. They found that firms that score high on material issues outperform companies that score poorly on material issues. We are primarily gathering inspiration from these studies and applying particular aspects from them in the context of M&A.

## 2. Literature review

## 2.1 M&A, ESG and Value Creation

A merger or acquisition can be a significant strategical decision for a firm, and the primary motive for such transactions is rooted in the synergy hypothesis (Damodaran, 2011; J. Y. Kim et al., 2011). Synergies arise when the value of the combined entity exceeds the value of the companies on a stand-alone basis and are often split into operational and financial synergies. Operational synergies consist of cost and revenue synergies related to economies of scale and scope, higher growth, reduction in administrative expenses, and increased pricing power. In contrast, financial synergies relate to tax optimization and debt capacity (Gaughan, 2017, p.136). The combination of these synergies results in higher cash flows and a lower cost of capital, leading to increased shareholder value.

M&A allows for a rapid change in business profile by penetrating new markets or geographies and can be a source of learning to improve ESG performance (Barros, Verga Matos, et al., 2021; Gaughan, 2017, p. 125-177). Consequently, companies use M&A as a tool to improve their ESG performance and meet the increasing demands from investors and legislators related to GHG emissions. By acquiring a relatively better ESG company than itself, the acquirer can gain additional knowledge to improve its environmental profile (Aktas et al., 2011; Tampakoudis & Anagnostopoulou, 2020). Moreover, Bose et al. (2021) find that acquirers with much carbon emissions are likely to offshore emissions by acquiring companies in countries where the risk of new and stricter legislation and punitive sanctions are less likely. These findings support our hypothesis that firms actively engage in M&A to manage their emission risk.

On the contrary, M&As are complex and can lead to value destruction (Gaughan, 2017, p.155). About 60% of transactions destroy shareholder value because of overpayment, inaccurately identifying and calculating company synergies, a poor post-merger integration process, high complexity, and difficult cultural fit (Attah-Boakye et al., 2021; Gaughan, 2017; Kengelbach et al., 2015; Lewis & McKone, 2016). The inherent difficulty of calculating synergies and assessing cultural fit makes M&A risky and can deteriorate the firm's operation. Consequently, Lewis and McKone (2016) find that organic growth through leveraging existing resources, customers, and capabilities is the best path to faster growth with limited risk. Moreover, not all firms can equally learn and transfer knowledge over to the target preventing an optimal

integration and synergy realization (Trichterborn et al., 2016). The inability to acquire and transfer knowledge to the target, combined with the inherent complexity of M&As, suggests that M&As might not be the most effective way of improving one environmental profile.

M&As, when either the target, acquirer, or both perform well within corporate social responsibility (CSR), is related to more synergistic deals because of a smoother integration process, reduced information asymmetry, better stakeholder alignment, and enhanced learning effect (Aktas et al., 2011; Malik, 2014). Consequently, acquirers see positive abnormal short-term returns and better operational improvement in such transactions (Feng, 2021; Krishnamurti et al., 2019). With environmental risk being a part of CSR, a high emission score, either the acquirer's or the target's, can be a source of additional synergies and enhance shareholder value as it measures its ability and effort to reduce emission-related externalities.

Moreover, better stakeholder alignment reduces exposure to new punitive and legislative risks. With the increasing price of carbon and carbon emissions almost being priced globally, the synergies related to emission management are becoming more evident (OECD, 2021). If emission-related costs keep increasing, the knowledge and ability to reduce emissions can benefit the acquirer beyond the upfront synergies from reducing emission risk.

On the contrary, low-ESG companies can improve their performance to a greater extent than high-ESG companies due to more substantial business image improvements, cost reduction, and regulatory and legal risk mitigation (Franklin, 2019; Tampakoudis & Anagnostopoulou, 2020). They found that companies with a low ESG score can improve more and, consequently, see better results. From this, we anticipate that the change in acquirers' emission score will affect their return as it reflects a company's improvement within emission management.

## 2.2 ESG, Risk, and Equity performance

The shareholder theory presented by Friedman (1970) argues that a firm's only responsibility is its shareholder. Therefore, companies should not engage in socially responsible behavior focusing on other stakeholders unless it results in greater long-run firm value. Following this view, unless the cost of a firm's exposure to carbon risk exceeds the benefits, a firm will not reduce its carbon risk if it does not increase profit further. Consequently, companies can rationally defend not complying with GHG emission regulations instead of complying as it can be more profitable and lead to higher shareholder value (Shapira & Zingales, 2018).

However, Hart and Zingales (2017) find that shareholders care about more than firm value and profits. Reducing a company's carbon emissions can maximize shareholder value even if it does not maximize its profit. This approach aligns with the stakeholder theory, which argues that organizations need to create value for all stakeholders and not just the shareholders (Freeman & McVea, 2001). Consequently, environmental initiatives can benefit a firm's shareholders as it improves its reputation and can be a source of knowledge, allowing for more innovation resulting in better performance.

Because companies can defend not complying with GHG emission regulations instead of complying as it can be more profitable, countries and other policymakers are passing stricter regulations forcing companies to internalize the cost of emission (Shapira & Zingales, 2018). In addition, there is increasing pressure from banks, customers, and investors for firms to comply with regulations, increasing the cost of emission-related externalities (Griffin et al., 2012; Matsumura et al., 2014). The increased cost of emissions makes it likely that more firms will reduce their environmental risk and internalize their emission cost.

The risk of harmful legislative, regulative, and fiscal action increases with improper CSR policies leading to a higher risk premium and cost of capital (Berman et al., 1999; Hillman & Keim, 2001; Liang & Renneboog, 2017; Ng & Rezaee, 2015). As a result, higher carbon emissions result in higher expenses as regulatory threats increase, the need for investments in abatement technologies increases, and one has to pay more in carbon taxes. Therefore, poor emission management can lead to lower margins and future cash flows, which reduce firm value.

A higher ESG rating is associated with lower exposure to systematic risk resulting in a lower cost of capital and higher firm value (Giese et al., 2015; Lodh, 2020; Ng & Rezaee, 2015). Banks look favorably upon the lower systematic risk, which can lead to better financing terms, lowering their cost of debt (Eliwa et al., 2021; Houston & Shan, 2019). Moreover, a stronger and more sustainable banking relationship can yield opportunities for firms to take on value-enhancing projects. Following this, firms that manage to reduce their environmental risk through M&A should see a lowered cost of capital, allowing them to make more profitable investments resulting in a higher firm value.

Abating carbon emissions and mitigating emission risk requires long-term strategic and financial commitments from shareholders, boards, and management (Bose et al., 2021; Kwon

et al., 2018). Moreover, the results from sustainable investments are not evident immediately, and when studying the effect of such investments, it is essential to have a long-term perspective (Kwon et al., 2018). Benabou and Tirole (2010) find that stakeholders are more responsive to investments that improve the firm's long-term perception and that shareholders will benefit from investments that succeed. Consequently, having a long-term perspective on a firm's emission risk appears to be material. Therefore, we investigate if an improvement in emission risk resulting from the M&A can lead to higher long-term returns.

In line with finance theory, which says companies should distribute or invest in projects that will maximize shareholder value (Berk & DeMarzo, 2017, p. 43), Khan et al. (2016) find that investments that reduce a company's sustainability risk are value-enhancing when the issue is material in the industry. This finding is an effort to reconcile the conflicting evidence of sustainability-related investment. Moreover, it supports that risk arising from emissions should be incorporated when making corporate decisions when it represents a material issue for the company. Consequently, the value enhancement of acquirers who reduce their emission risk through M&A is likely to be linked to the materiality of the GHG emission issue in their industry.<sup>3</sup>

Investment in improving a firm's environmental footprint is usually costly, reducing shortterm cash flow and lowering short-term equity returns (Krüger, 2015). He explains that this reaction can come from executives highlighting themselves as "green" leaders on behalf of the shareholders. Moreover, the benefit from environmental investments is usually more apparent in the longer term, which is more challenging for investors to price correctly (Kwon et al., 2018). If one considers that short-term investors dominate the market, long-term environmental-oriented investments should yield lower returns at the announcement (Krüger, 2015).

Moreover, newer evidence suggests that investors demand a carbon premium and that firms with more emissions see higher returns than companies with lower carbon emissions (Bolton & Kacperczyk, 2021). Their finding cannot be explained by other known risk factors, suggesting that investors are already demanding compensation for their exposure to carbon emission risk. This finding aligns with the risk-return trade-off, which states that returns should increase if risk increases. The carbon premium can also explain why Krüger (2015)

<sup>&</sup>lt;sup>3</sup> We use the SASB materiality map to measure the importance of GHG emissions in the different industries.

found the announcement of environmental-related investments to yield negative returns. Thus, one would expect lower announcement returns for firms that improve their emission score as they become less risky.

## 3. Research questions

This thesis explores if acquirers can create value by improving their emission risk through M&A. Therefore, we will first explore if companies can use M&A to improve their emission risk. Next, we investigate how the change in the acquirers' emission risk resulting from the transaction affects short and long-term returns while accounting for industry materiality.

M&As can be a significant investment for a firm, bring operational and financial synergies, and allow the firm to enter new segments or geographies while enhancing shareholder value (Gaughan, 2017, p. 125-177). Previous studies have found that both the acquirer and the target can learn from each other's sustainability policies, knowledge, and culture, leading to an enhanced sustainability performance (Aktas et al., 2011; Barros, Verga Matos, et al., 2021; Malik, 2014). Moreover, Bose et al. (2021) find that firms use M&A to offshore their emission risk, where the risk of future regulations and punitive actions is less probable. With M&A allowing for significant and rapid changes to a business profile, and previous studies finding that firms use M&A actively to mitigate or shift their environmental risk, we believe firms use M&A to reduce their emission risk.

The learning effect is more profound when the target has a higher ESG score than the acquirer (Tampakoudis & Anagnostopoulou, 2020). By acquiring a target with a higher score, the acquirer can learn from their culture, policies, technology, and knowledge, incorporating these benefits into their existing operation and improving their sustainability performance. Therefore, we include the relative difference in emission score between the target and the acquirer to explore if the same relationship exists with emission risk.

#### **3.1 Hypothesis 1a)** Firms use M&As to improve their emission risk

## **3.2 Hypothesis 1b)** The change in acquirers emission score is positively correlated with the relative difference in emission score between the target and the acquirer

M&As can create value for both the acquirer and the target through operational and financial synergies, and a high CSR and ESG performance of both the acquirer and the target can lead to higher announcement returns due to a smoother integration, better stakeholder alignment, and enhanced learning effect (Aktas et al., 2011; Gaughan, 2017, p. 125 - 177; Malik, 2014). Moreover, sound environmental management reduces a firm's exposure to future governmental regulations and punitive actions, which protect their future margins and cash

flows, reducing their systematic risk (Berman et al., 1999; Giese et al., 2015; Hillman & Keim, 2001). Lower systematic risk grants firms better and cheaper access to capital, allowing them to invest in more extensive and value-enhancing projects, increasing their value (Houston & Shan, 2019). Investors and banks look favorably upon this, resulting in a lower cost of capital and increasing firm value (Eliwa et al., 2021; Lodh, 2020; Ng & Rezaee, 2015).

On the contrary, following fundamental finance theory, lower risk should result in lower returns. This is supported by Bolton and Kacperczyk (2021), who find that more pollutive firms see higher returns than less pollutive firms and attribute this to a carbon premium. They found carbon premium to be present, controlling for other known risks factor. Additionally, Krüger (2015) found the market to react negatively to the announcement of investment aiming to improve a firm's environmental risk. He attributes this to the significant short-term outlay of cash and the risk of executives trying to become known as "green" leaders at the expense of the shareholders. However, the effect of improved emission risk can depend on the materiality of the issue a firm operates in. Khan et al. (2016) found that good performance in sustainability-related matters is only value-creating if the industry's specific sustainability issue was material.

Nonetheless, due to the increased environmental focus among investors, and the increasing emission-related regulations, we expect firms who engage in M&A and improve their emission score when it is material for their industry will see positive short-term abnormal returns.

## **3.3 Hypothesis 2a)** Companies improving their emission score through M&A when it is material in the acquirer's industry, will see abnormal short-term returns.

The effect on the acquirer's emission score resulting from the M&A might not be evident immediately (Barros, Verga Matos, et al., 2021). Supporting this, Kwon et al. (2018) find that when studying the results from sustainable strategies, it is essential to have a long-term perspective as such strategy might not yield results in the short term. The lagging effect when investing in improving a firm's sustainability is supported by Duarte and Barros (2018). They find that acquirers only see an improvement in their ESG score the year after the transaction and attribute this to the increasing learning effect.

Short-term investors tend to sell off after firms announce environmental-related investments, leading to negative returns (Krüger, 2015). He argues that this comes from the risk of managers

trying to "greenwash" themselves, the large initial cash outlay and that investors find it challenging to value the long-term benefits from such investments accurately. If the investment is sound, the benefits will be apparent in the long run and can lead to additional returns to compensate for the sell-off due to the lack of visibility at the announcement. Therefore, we investigate if investments in improving a firm's sustainability are better reflected in long-term returns.

**3.4 Hypothesis 2b)** Companies improving their emission score through M&A when it is material in the acquirer's industry, will see abnormal long-term returns.

## 4. Data providers and sample selection

To collect the data needed for this thesis, we used the Refinitiv ESG database for emissions scores, Refinitiv Worldscope database for financial data, and Refinitiv SDC Platinum Mergers for transactions. The following sections will discuss why we chose the Refinitiv ESG database for our ESG data and their scoring methodology. After that, we will elaborate on how we created the sample used in this paper.

## 4.1 Choice of ESG rating provider

We will utilize the Refinitiv ESG database because they have scores dating back to 2002, currently covering 70% of the global market cap across 500 ESG metrics, and offer specific emissions and environmental issues measures, which is our primary focus (Refinitiv, 2021). Their scores are data-driven and account for the most material industry metrics while minimizing biases that arise from transparency and company size. Over 150 research analysts retrieve data from annual reports, company websites, NGO websites, stock exchange files, CSR reports, and news sources (Refinitiv, 2021). Moreover, by scoring firms relative to their peers, the Refinitiv data alleviates some measurement issues using absolute scores (Chatterji et al., 2009).

With little score convergence, it is challenging to assess which provider is the most accurate, and we find the detailed and relative score from Refinitiv appropriate. Evaluating and scoring a company's ESG profile requires firms to disclose necessary information, and some measures can be subjective, making scoring inconclusive. Consistent with extensive literature, Chatterji et al. (2009) find that the measurement of a company's environmental management systems is of low validity, and the scores do not reflect publicly available information. The inherent difficulty of providing accurate scores is emphasized by Dorfleitner et al. (2015). They found no convergence in ESG scores when comparing ESG scores from Refinitiv, Bloomberg, and Morgan Stanley Capital International (MSCI).

#### 4.1.1 Refinitiv emission score

This thesis focuses on how changes to the acquirer's emission score affect their performance. Therefore, we will look deeper into what the emission score measure and how it is constructed. The emission score "measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes" (Refinitiv, 2021). While it looks like the emission score mainly measures a company's commitment towards reducing emissions, it also includes a company's total GHG emissions and hazardous waste. From this, a company's emission score can be considered a proxy for the risk associated with poor emission management and its performance in reducing its emissions.

The quantitative and measurable pillars included in the emission score make it less prone to subjective assessment and should reduce the discrepancy among the data providers. The emissions score comprises 28 measurable factors and is weighted depending on the industry materiality of these issues. Next, a company's performance on these 28 matters is evaluated before the firm receives a score between 0 and 100 (Refinitiv, 2021). This score is based on the relative performance of its sector peers, and the formula for the percentile rank is displayed below. Moreover, the emission score captures a firm's total emissions, which is easier for investors to value as emissions are priced almost globally (OECD, 2021). Thus, we find it feasible that the change in emission score can affect acquirer returns. The definition of the three subcategories that makes up the environmental pillar is listed in Table 15.

 $Score = \frac{no. of companies with a worse value + \frac{no. of companies with the same value included in the current one}{2}}{no. of companies with a value}$ 

Because Refinitiv requires a certain level of reporting to score a company, there is some bias in our data as scoring is non-random. This bias results in both the acquirers and the control groups being likely to be "high" performers within the environmental performance. With acquirers having an ESG score might be more environmentally aware than other firms, the choice of a target can be non-random. Also, the control group's emission score might increase faster than the actual market, neglecting the positive effect an M&A could have on the acquirer's emission score compared to the control group. However, with Refinitiv covering over 70% of the global market cap, this selection bias is reduced. Moreover, ESG disclosure may be correlated with financial disclosure, potentially explaining any abnormal performance.

### 4.2 Introduction to SASB

We use Sustainability Accounting Standards Board (SASB) to measure the materiality of GHG emissions in the industries in our final sample. This allows us to look at how the change in acquirers' emission score affects their performance, accounting for the importance of GHG emissions. To retrieve the appropriate industry for our final sample of transactions, we looked up the companies from the Sustainability Accounting Standards Board (SASB) website, using the companies' ISIN numbers.

SASB is an organization that guides companies on reporting their ESG performance properly and identifying material sustainability issues for different industries (SASB, 2021). They divide the challenges into 26 sustainability-related business issues known as General Issue Categories (GIC) that are likely to affect companies' financial condition or operating performance within different industries. SASB conducts an evidence-of-materiality test for each topic, and the test components are evidence of interest, financial impact, and forward impact adjustments. When SASB has completed the test, they publish the results for debate, and then the Standards Council reviews them to ensure consistency, completeness, and accuracy (SASB, 2021). See Table 16 for a complete list of the industries.

## 4.3 Sample selection

Our data on acquisitions come from the Refinitiv SDC database, which contains data on over 1.1 million M&As since the 1970s. Because Refinitiv started scoring public companies on their ESG performance in 2002, our sample selection will include M&As between public companies from 01.01.2002 – 01.06.2021. Because we investigate the long-term returns and changes in acquirers' emission scores, we require the deal to be completed. To capture the effect of the control premium and the deal to be of significant size, we require the deal size to exceed USD 50 million and that the acquirer must own <50% before the transaction and >90% after the transaction (Bereskin et al., 2018; Bouzgarrou & Navatte, 2013; Gregory, 2003). Moreover, to retrieve the financial data needed, we require both the acquirer and the target to have a PermanentID. Finally, we exclude transactions with financial buyers<sup>4</sup> and transactions where the target's or acquirer's macro industry is listed as: government and agencies<sup>5</sup> (Farooq

<sup>&</sup>lt;sup>4</sup> As defined by the SDC database

<sup>&</sup>lt;sup>5</sup> As defined by the SDC database

Ahmad et al., 2015). After applying these restrictions, but before we screened on emission scores and financial variables, we ended up with 6,455 transactions.

Next, we add accounting data and remove transactions where the acquirer does not have an emission score in the years t-1, t, and t+1 as we explore how the change from t-1 to t and t to t+1 affects their returns, leaving us with 1,272 transactions. We need the acquirers' stock returns for hypothesis two, leaving us with a sample of 1,169. Hypothesis 1b requires the target to have an emission score, leaving us with a sample size of 206. The sample creation is summarized in Table 1 below.

Table 1 - Sample creation and criteria

Filter	Number of deals
Trasactions from 01.01.2002 - 01.06.2021, where acquirer owns less than 50% before and more than 90% after the transaction	355,005
Both acquirer and the target are/were publicly traded	-343,123
Transaction value must exceed USD 50 million	-3,262
Do not include financial buyers	-1,746
Both acquirer and target need to have a permanentID	-419
Number of deals before applying company data	6,455
Acquirer having an emission score	-5,053
Adding financial data	-233
Final sample size	1,169
Sample size when target also have an emission score	206

#### Table 2 - Deals summarized by SDC macro industry

			Acquirer Emission	<b>Target Emission</b>
Macro Industry	Acquirer	Target	score T-1	score T-1
Consumer Products and Services	43	44	45.8	45.3
Consumer Staples	64	63	61.2	50.7
Energy and Power	138	143	56.1	47.9
Financials	144	138	51.6	38.5
Healthcare	169	183	66.0	39.9
High Technology	165	217	65.5	33.6
Industrials	147	140	51.5	41.5
Materials	201	182	55.4	44.3
Media and Entertainment	49	43	58.7	56.1
Real Estate	42	43	58.3	34.2
Retail	51	38	63.2	57.3
Telecommunications	59	38	62.4	43.1

Source: Refinitiv and SDC

			Mean Deal	Mean Acquirer	
Deal Announcement Year	Number of Deals	Percentage of Total	Value (USDm)	<b>Emission Score Year</b>	Mean CAR
2003	24	1.89%	3,144	52	0.1%
2004	18	1.42%	6,450	46	-0.4%
2005	52	4.09%	5 <i>,</i> 899	58	-0.3%
2006	95	7.47%	5,224	54	-0.2%
2007	79	6.21%	3,034	64	-0.7%
2008	72	5.66%	3,413	58	-0.9%
2009	69	5.42%	3,187	59	-1.9%
2010	96	7.55%	1,869	59	-0.4%
2011	83	6.53%	2,444	56	-0.5%
2012	75	5.90%	2,260	62	-1.3%
2013	50	3.93%	2,433	61	0.6%
2014	87	6.84%	4,056	56	0.6%
2015	95	7.47%	6,286	58	-1.1%
2016	99	7.78%	5 <i>,</i> 896	60	-0.9%
2017	99	7.78%	4,324	50	-0.3%
2018	101	7.94%	5,177	61	-1.9%
2019	75	5.90%	4,634	64	0.0%
2020	3	0.24%	3,357	54	-5.2%

Table 3 - Deals by year of announcement

Source: Refinitic and SDC

Note: The few transactions in 2020 and none in 2021 comes from us requiring the acquirer to have an emission score in T+1

#### Table 4 - Summary statistics

Variable	Unit	Min	Mean	Median	Max	Standard deviation
Acquirer: Emission Score	Number	0.4	61.4	67.2	99.7	28.5
Target: Emission Score	н	0.5	44.0	39.4	98.4	27.5
Change in emission score	п	-65.2	3.3	1.2	81.7	14.4
Acquirer Financial Variable	s					
Price/Book	Number	-220.0	3.1	2.2	217.4	10.8
Debt/Assets	Percentage	0%	24%	22%	89%	15%
EBITDA/Assets	п	-111%	13%	12%	81%	10%
R&D/Assets	п	0%	2%	0%	27%	4%
Sales Growth	н	-100%	30%	15%	5184%	187%
Total Assets	USD Millions	189.8	70,027	17,310	1,884,318	189,482
Total Cash	п	0.0	446	50	41,346	2,180
Target Financial Variables						
Price/Book	Number	-211.4	3.9	1.7	1,489.1	43.6
Debt/Assets	Percentage	0.0	0.2	0.1	3.4	0.3
EBITDA/Assets	н	-917%	5%	8%	417%	36%
R&D/Assets	н	-1%	5%	0%	754%	24%
Sales Growth	н	-100%	103%	18%	34365%	1084%
Total Assets	USD Millions	0.0	8,877	621	1,323,701	56,936
Total Cash	н	0.0	446	50	41,346	2,180

## 5. Methodology

## 5.1 Mapping of materiality

We are utilizing the SASB materiality map to measure the importance of emissions for each industry. The SASB GHG emission sustainability issue focuses on relevant GHG issues that companies within the different industries have. The materiality of these issues is split into three levels (SASB, 2021). SASB illustrates the materiality with three shadings of grey, according to the definition listed in Table 18. To measure materiality in our regressions, we translated the shadings of grey into numbers. Depending on the materiality, we gave each industry a 0, 0.5, or 1, where 0 means not material and 1 means material. See Table 16 for an overview. Our sample has 77 industries and materiality of only 0 and 1. SASB's definition of GHG sustainability issue is listed in Table 15.

## 5.2 Hypothesis 1

Before assessing if companies who improve their emission score through M&A see abnormal short and long-term returns, we explore if M&A can affect a company's emission score. Through an Ordinary Least Squares (OLS) model, we compare the change in emission scores that the acquirers see from the acquisition against their change in emission score when they have not undergone an acquisition. After this, we use a difference-in-difference to compare our group of acquirers' emission score against the universe of companies with an emission score that have not undergone an acquisition. Next, we perform the same difference-in-difference-in-differences regressions using a propensity score matched control group to allow a more casual interpretation. Lastly, we assess if the target's emission score as a continuous treatment.

We include the relative difference in emission score for all our regressions. This allows exploring the effect the target's emission score has on the change in the acquirers' emission score. It makes the treatment factor more granular, as it allows us to account for the amount of treatment the acquirer receives, not only doing an M&A. Moreover, it can speak for the motivation of the transaction, as acquirers who incorporate emission risk in the acquisition are likely to acquire more environmentally aware firms (Barros, Verga Matos, et al., 2021; Tampakoudis & Anagnostopoulou, 2020). However, when including the relative difference as

continuous treatment, we lose a significant number of transactions. There were only 206 transactions where the acquirer and the target had an emissions score. Because we use the same estimation techniques to test hypotheses 1a and 1b, we describe the methodology jointly.

The first OLS measure if our group of acquirers improved their emission score more in the year of or the year after the transaction than what they do in years without a transaction. Our dependent variable is the one-year change in emission score. Following Barros and Verga Matos et al. (2021), the deal variable is a binary variable taking place in time T and T+1, the year of the deal, and the year after. By including T+1 in our regression, we control the lag effect that can arise when acquiring a firm and is frequently used in the finance literature (Barros, Guedes, et al., 2021; Duarte & Barros, 2018). Next, we redo the OLS described above using the relative difference in emission score between the target and acquirer as a continuous treatment.

Relative difference in emission 
$$score_i = \frac{Target \ emission \ score_i}{Acquirer \ emission \ score_i} - 1$$

For both the OLS described, the data is unrestricted, and at the minimum, we require to have data of the acquirer one year before and one year after the transaction. This results in 2,622 firm-year observations and 1,169 unique transactions in the unrestrictive test. When using the relative difference between the acquirer and the target's emission score, we have 886 firm-year observations and 206 unique transactions.

We use the acquirers' logarithm (log) of total assets, debt to assets, capital expenditure to total assets, R&D to assets, and price-book ratio as financial control variables in both regressions. The log of total assets and capital expenditure to total assets is included as company size and investments are related to environmental sustainability (Balasubramanian et al., 2021). R&D to assets can be a proxy for innovation, and we argue that more innovative companies are likely to see higher emission scores (Gault, 2018; Greenhalgh & Rogers, 2010). The price to book ratio says something about a firm's growth opportunities, which is linked to innovation (Tohidi & Jabbari, 2012). We include debt to assets because better-governed firms have less leverage which can dictate how much a firm is willing to invest in improving its emission risk (Sharma et al., 2020; Utz, 2019). The relative deal size is included as a relatively larger target will become a more significant part of the post-transaction company and impact the "new" firm's emission risk more. Lastly, we account for country, and time-fixed effects as these

factors can explain the innovation level of a company (Balasubramanian et al., 2021; Cohen et al., 2021).

#### Change in Emission Score<sub>i</sub> = $\beta_0 + \beta_1 M \& A_i + \beta_2 F_i + \beta_3 D S_i + \theta_i + \varepsilon_i$

M&A is the number of registered acquisitions for the individual company until that time in the data, F is a vector accounting for the acquirers' financial characteristics, DS is deal-specific characteristics, and  $\theta$  is the time fixed effects.<sup>6</sup> We redo this regression but replace M&A with the relative difference in emission score as a continuous treatment.

We include the fixed effects that do not violate the VIF-test, and the results are presented in Table 19 and Table 20. The remaining variables are below the broadly accepted cut-off level for the generalized variance inflation factor of 10 (Wooldridge, 2012, p. 98). Moreover, we use a Breusch-Pagan test to test for heteroskedasticity and for the difference-in-differences, we use heteroskedasticity-robust standard errors.

We will estimate a difference-in-difference model using balanced data to correct for unobserved variables and unbalanced data bias that can affect the OLS. In the difference-indifference regression without propensity score matching, we compare the emission score between our sample of acquirers and a control group in the pre and post-treatment period. The interaction *Treatment x Post M&A* is the primary variable of interest. Such an interaction term is valuable because it can indicate if a third variable influences the relationship between the independent and dependent variables (Cox, 1984). This variable tells how the emission score of our treatment group has changed after the M&A compared to a broader control group. The pre-M&A period is from T-3 to T-1 (years), and the post-M&A is from T to T+2. We ensure the data is balanced by requiring the treatment group to have observations of their emission score for six consecutive years. As with the OLS, we repeat the regressions using the relative difference in emission score as a continuous treatment.

A post-treatment period of three years (T, T+1, and T+2) in our difference-in-difference allows us to investigate a more long-term effect on emission score when doing an M&A. The longterm change in emission score can tell us if companies use M&A to learn from the target to realize additional synergies and reduce their emissions or improve their environmental profile.

<sup>&</sup>lt;sup>6</sup>We tried including industry-fixed effects, but this led to values violating the multicollinearity cut-off.

The control group consists of all companies with an emission score in the Refinitiv database (5,683 firms). We ensure that the control companies have not made an acquisition by adding a dummy variable if a company has made any acquisitions in the last two years. The dummy variable is based on our initial sample of 6,455 transactions.

Using a difference-in-difference estimator enables us to simulate experimental research by comparing the result from the treatment group with the control group across pre-treatment and post-treatment periods (Wooldridge, 2012, p. 455-458). Moreover, the difference-in-difference reduces selection bias, systematic bias, and the effect of external factors, which impact the OLS, adding robustness to our findings. The difference-in-difference estimator assumes no anticipation of the treatment and parallel trends between the treatment and control group in addition to the OLS assumptions (Wooldridge, 2012, p. 230). To see if there are parallel trends, we graph the development in emissions scores. From Table 5 below, we see that the treatment and control groups' emission score moves parallelly, and this assumption for the difference-in-difference appear to hold.

#### Table 5 - The development in emission score of our treatment and control firms

We are using the fixed effect difference-in-difference model as we observe the same sample of transactions for each period of the panel data (Wooldridge, 2012). Not all the induvial terms used to create an interaction term will receive a coefficient when using the fixed effect estimator. This comes from the variable not having any variation throughout the time series. The alternative would be to use pooled OLS. However, we do not find it appropriate because this selects a different sample of transactions for each period of the panel data and does not measure the individual firm's changes (Wooldridge, 2012, p. 454).

$$Emission \ Score_i = \beta_0 + T_i \ x \ Post \ M\&A + \beta_1 F_i + \beta_2 DS_i + \gamma_i + \theta_i + \varepsilon_i$$

T is a dummy variable for companies being a treatment company or not and is interacted with Post M&A. F is a vector accounting for the acquirers' financial characteristics; DS accounts for deal-specific characteristics;  $\gamma$  is firm-specific fixed effects, and  $\theta$  is time-fixed effects. All variables that interact will have their individual coefficient, but they are excluded in the equation above for the visuals. When using continuous treatment, D<sub>T</sub> is replaced with  $\frac{Target}{ACQ}ES$ , which is the relative difference in emission score.

We add propensity score matching to simulate randomization allowing for a more casual interpretation. This reduces the bias in the data as the level of emission score (treatment outcome) can have changed due to factors predicting the treatment (M&A) rather than the treatment effect. After obtaining a propensity score for all companies, each acquiring firm is matched with one control firm using the nearest-neighbor method. Next, we remove the pairs that are too different, with a difference of two standard deviations being the criteria. After obtaining the new control group, we perform the exact difference-in-difference estimations described above.

We use a logit regression illustrated in the equation below to find a matching company. The dependent variable is whether a company will likely acquire another firm the following year. Following Golubov et al. (2013) and Krishnakumar and Sethi (2016), we find matching companies based on the log of total assets, debt to total assets, EBITDA to total assets, the price-book ratio, cash, and R&D to total assets, as these are known determinants of the likelihood of acquiring companies. Moreover, we add country, year, and industry fixed effects.

Propensity Score<sub>i</sub> = 
$$P(M\&A)_i = \beta_0 + \beta_1 F_i + \alpha_i + \theta_i + \lambda_i + \varepsilon_i$$

F is a vector accounting for financial characteristics;  $\alpha$  is industry-fixed effects;  $\theta$  is time-fixed effects, and  $\lambda$  is country fixed effects.

Variable	Control - Mean	Treatment - Mean	Difference	T-value
Pre matching				
Ln (Size)	22.5	23.9	-1.4	-59.0
Leverage	0.3	0.2	0.0	1.5
Profitability	0.1	0.1	0.0	0.1
P/B	3.2	3.3	-0.1	-1.3
Ln (Cash)	19.5	20.9	-1.4	-56.9
R&D/Assets	0.01	0.02	0.0	-4.0
Emission Score T-1	34.5	64.0	-29.5	-286.8
Post matching				
Ln (Size)	23.6	23.8	-0.3	-8.1
Leverage	0.3	0.3	0.0	0.0
Profitability	0.1	0.1	0.0	-0.2
P/B	3.2	3.3	-0.1	-1.0
Ln (Cash)	20.7	20.9	-0.2	-5.6
R&D/Assets	0.02	0.02	0.0	-0.5
Emission Score T	55.76	63.62	-7.9	-53.9

Table 6 - Descriptive Statistics - Covariates Before and After Matching

### 5.3 Hypothesis 2 a

We will use an OLS regression and a fixed effect difference-in-difference model to test how a change in acquirers' emission score affects their short-term returns. The difference-indifference estimator will use a broader control group and a propensity score-matched control group. Lastly, we perform a quadruple difference-in-difference to test how the change in emission score that arose from the acquisition affects returns. We will only look at the companies in our sample of acquirers for the OLS and difference-in-difference. However, the quadruple difference-in-difference will use the same control group as in hypothesis one.

The OLS uses an interaction term between materiality and the one-year change in acquirers' emission score, from T-1 to T and T to T+1, as the primary explanatory variable of their cumulative abnormal return (CAR). The CAR is measured from T-2 to T+2 (days). When available, we use the relative difference between the acquirer and the target's emission score in T-1. This difference is observable at the announcement date and can be easier for investors to incorporate when evaluating the acquisition. Following Bena and Li (2014) and Bereskin et

al. (2018), we use the acquirers` T-1 log total assets, price-to-book, return on assets, leverage, two-year sales growth, log cash, and R&D-to-assets as firm-specific control variables, and payment method, relative-deal size and, industry relatedness as deal-specific variables. We further include fixed effects that do not violate the VIF test. See Table 15 for the definition of the variables.

$$CAR_{i} = \beta_{0} + \Delta ES_{i} \times M_{i} + \beta_{1}F_{i} + \beta_{2}DS_{i} + \lambda_{i} + \theta_{i} + \varepsilon_{i}$$

 $\Delta ES$  is the change in emission score and is interacted with M, which is industry materiality. F is a vector accounting for the acquirers' financial characteristics; DS accounts for deal-specific characteristics;  $\lambda$  is country-fixed effects, and  $\theta$  is time-fixed effects. All variables that interact will have their individual coefficient, but they are excluded in the equation above for the visuals. We redo the estimator by replacing  $\Delta ES$  with  $\frac{Target}{ACQ}ES$ , which is the relative difference in emission score.

The fixed effect difference-in-difference without propensity score matching investigates the difference in a company's return in the period before the transaction to after the transaction and utilizes the emission score change as a continuous treatment. A treated company will not have a CAR in time = 0 (before the transaction). Consequently, we use their abnormal return from t-15 to t-11 as pre-transaction returns. We utilize a holdout window of eight days, similar to estimating short-term returns described in section *4.4.1*. The abnormal announcement return is calculated from t-2 to t+2. With the acquirer's abnormal return being the dependent variable, we measure the degree to which the treatment and the change in emission score affect returns. We also test for materiality while controlling for the firm-specific and time-fixed effects.

#### Abnormal Return<sub>i</sub> = $\beta_0$ + *Post M&A x* $\Delta ES_i x M_i + \beta_1 F_i + \beta_2 DS_i + \gamma_i + \theta_i + \varepsilon_i$

In the next step, we will perform the same difference-in-difference equation described above but utilize propensity score matching to create a control group. Because the treatment is the change in emission score, the control group is based on the likelihood of seeing a similar change in emission score. This matching is done on the same variables we argue are relevant for change in emission score in hypothesis one. After finding a match for each company, we remove pairs that we do not find similar enough, following the same methodology as hypothesis one.

Propensity Score<sub>i</sub> = 
$$\beta_0 + \beta_1 F_i + \alpha_i + \lambda_i + \theta_i + \varepsilon_i$$

In the last estimation technique, we combine research questions one and two. Here we test how the change in emission score that arose from the acquisition affected acquirers' CAR using a quadruple difference-in-difference regression. From this estimator, the variable of interest is *Post M&A x*  $\Delta ES x M x T$ . The new variable T is a dummy variable for companies being a treatment company or not. We use the same control group as found in the propensity score matching from hypothesis one.

Abnormal Return<sub>i</sub> =  $\beta_0$  + Post M&A x  $\Delta ES_i x M_i x T_i + \beta_1 F_i + \beta_2 DS_i + \gamma_i + \theta_i + \varepsilon_i$ 

## 5.4 Hypothesis 2 b

We use an OLS estimator to test for long-term abnormal returns, 36 months, and we will try various windows of change in emission scores as our explanatory variable. As with the short-term analysis, we create an interaction term that accounts for the materiality of emission-related issues in the industries. When calculating the long-term abnormal returns, we use the Jensen-alpha approach. The benchmark model used as the market will be the appropriate country or region Fama-French 5 factor model.

Because investments in sustainability take longer to materialize and the effect on ESG scores from M&A has a lag, the impact on returns might be more apparent in a long-term analysis (Barros, Verga Matos, et al., 2021; Kwon et al., 2018). The long-term change in emission score resulting from the acquisition can tell us if companies use M&A to learn from the target to realize additional synergies and reduce their emissions or improve their environmental profile.

Long term return<sub>i</sub> = 
$$\beta_0 + \Delta ES_i \times M_i + \beta_1 F_i + \beta_2 DS_i + \lambda_i + \theta_i + \varepsilon_i$$

 $\Delta ES$  is the change in emission score and is interacted with M, which is industry materiality. F is a vector accounting for the acquirers' financial characteristics; DS accounts for deal-specific characteristics,  $\lambda$  is country-fixed effects, and  $\theta$  is time-fixed effects. All variables that interact will have their individual coefficient, but they are excluded in the equation above for the visuals. We redo the estimator by replacing  $\Delta ES$  with  $\frac{Target}{ACQ}ES$ , which is the relative difference in emission score, but without  $\lambda$  to secure that all GVIFs are below 10.

#### 5.5 Short-term abnormal return measurement

We will use the event study methodology to measure how a change in acquirers' emission score affects their short-term cumulative abnormal return (CAR). To calculate the CAR, we use the market model. Short-term event studies are generally well specified and have a strong performance in detecting abnormal performance. This precision mainly comes from the relatively small chance of miscalculating the abnormal returns due to errors in adjusting for risk. Therefore, short-term event studies are an efficient tool to test market efficiency and better understand corporate policy decisions (Kothari & Warner, 2007).

We will use the market model to measure the short-term CAR in the event study. According to Mackinlay (1997), the market model and the constant expected returns is the most common models used in short-term event studies. However, the market model offers an improvement versus the constant mean returns models, as it removes the portion of the returns related to the variation in the market returns (Mackinlay, 1997).

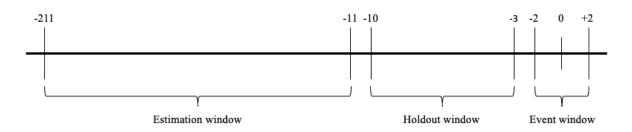
When calculating their CAR, we use the acquirers' respective countries' main index as the market portfolio. The market model assumes a stable linear relationship between the market return and the security return and is known as a single index model. Consequently, one should use a broad stock index as the market portfolio, where the S&P 500 is commonly used (Mackinlay, 1997).

$$R_{if} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$
$$E(\varepsilon_{it}) = 0 \qquad VAR(\varepsilon_{it}) = \sigma_{\varepsilon_i}^2$$

 $R_{i,t}$  = the return of stock i at time t  $\alpha_i$  = the assets excess return relative to the market.  $R_{m,t}$  = is the return of the market index at time t,  $\beta_i$  = the covariance of the stock with the market  $\varepsilon_{i,t}$  = the residuals for stock i at time t.

To estimate the expected returns for the acquirers, we use daily returns within a 200-day estimation period (t = -211 to t = -11). The length of the estimation window is inspired by Chang (1998), Masulis et al. (2007), and Moeller and Schlingemann (2005). The eight days preceding the acquisition announcement are excluded and are called a holdout window. Utilizing a holdout window is common in event studies, as information regarding the corporate event is often leaked, allowing the capital market to adjust accordingly. To calculate the CARs,

we follow Brown and Warner (1985) and utilize daily returns in as five-day event-window (t = -2, to t = +2, and t = announcement day).



### 5.6 Long-term abnormal return measurement

Because the Jensen-alpha approach is receptive to classical statistical inference, we find this approach appropriate when measuring long-term returns (Kothari & Warner, 2007). We follow Kothari and Warner (2007) when estimating long-term abnormal returns and use the appropriate Fama-French five-factor model as the benchmark. Long-horizon event studies must deal with several fundamental issues, including risk adjustments and expected/abnormal returns modeling, the aggregation of security-specific abnormal returns, and adjusting the statical significance of abnormal returns (Kothari & Warner, 2007). The most common methods to measure long-term returns after an event are the buy-and-hold abnormal return (BAHR) and the Jensen-alpha approaches. Each model has its strengths and weaknesses, making neither uniformly accepted as better than the other (Petrova et al., 2010).

A strength of the Jensen-alpha monthly calendar-time portfolio is that it is less vulnerable to the bad model problem. Further, all cross-correlations of event firms' abnormal returns are accounted for in the portfolio variance. Lastly, the estimator is receptive to classical statistical inference as the estimator closely follows a normal distribution (Mitchell & Stafford, 2000). However, the Jensen-alpha approach has been critiqued for being biased toward finding results consistent with market efficiencies (Loughran & Ritter, 2000). Loughran and Ritter further critique this approach, arguing that executives time corporate events (M&As) to exploit potential mispricing and that the calendar-time portfolios do insufficiently incorporate this.

The BAHR approach can be favored as it more closely resembles an investor's investment experience than other approaches that are based upon monthly rebalancing portfolios to measure risk-adjusted returns (which the Jensen-alpha approach is). On the other side, the BAHR approach suffers from its dependency and accuracy on matching an event firm with a

non-event firm. To allow for statistical inference, one must assume that event firms differ from similar non-event firms only because they experience the event. Moreover, acquisitions are not random events, and to undergo such an event is unlikely to be exogenous regarding the past performance and expected returns. This potential fundamental difference increases the risk of the matched firms being systematically different, and expected returns should differ (Kothari & Warner, 2007).

When calculating returns, we use monthly returns and start measuring the month following the acquisition announcement, following Kothari and Warner (2007). Instead of forming portfolios of returns, we will estimate the abnormal returns for each acquirer in our sample. In our sample, we have 32 countries, and not all countries have their own Fama-French five factors. Therefore, we will regress the acquirer monthly returns on the region or country-specific Fama-French five-factors as we see fit.<sup>7</sup> We realize this might not be an ideal way of measuring long-term abnormal returns and that we could create the country-specific Fama-French five factors. However, we argue that if our results are genuinely abnormal, it should not be of the essence if we use the region or country-specific Fama-French five-factor Fama-French data from their website and estimate the following model.

$$R_{i,m} - R_{f,m} = \alpha_i + \beta_i \left( R_{mkt,m} - R_{f,m} \right) + s_i (SMB_m) + h_i (HML_m) + r_i (RMW_m) + c_i (CMA_m) + \varepsilon_{i,t}$$

## 5.7 Endogeneity concerns

#### 5.7.1 Instrumental variable

To correct potential endogeneity problems related to the change in acquirers' emission score, we create an instrumental variable (IV) and perform a two-stage least squared regression (2SLS). This IV regression is performed for the OLS in hypotheses 2a and 2b. A firm's voluntary disclosure affects emissions scores from Refinitiv (Refinitiv, 2021). We also suspect firms who properly disclose emission-related information also disclose and report financial information adequately. Higher quality and a more transparent ESG and financial reporting are associated with better CSR performance (Y. Kim et al., 2012). This is further related to lower cost of capital and positive abnormal returns for acquirers in a short-term window (Botosan, 2006; Y. Kim et al., 2012; Krishnamurti et al., 2019). With this in mind, we suspect

<sup>&</sup>lt;sup>7</sup> See Table 17 for an overview.

that the emission score variable suffers from an endogeneity problem. For our instrument to be valid, it must meet two requirements: It must be relevant and cannot correlate with the error term (Wooldridge, 2012, p. 512).

Relevance:  $Cor(Z_i, Emission \ score_t) \neq 0$ Exogeneity:  $Cor(Z_i, \mu_i) = 0$ 

Inspired by Cheng et al. (2014), we created the instrumental variable, one year change in country-year mean. The rationale for using this variable is that we believe companies' emission performance is affected by a country's legislation and emission policies (Ioannou & Serafeim, 2012). The country-year variable is time-dependent because countries' regulations related to emissions change over time. We removed the focal firm's score from the calculation to remove the potential endogeneity associated with the targets and acquirers' emission scores. This should make our instrumental variable meet the exogeneity requirement. However, we cannot exclude the possibility that the omitted variable bias related to the company's emission score, such as quality and transparent financial reporting, is coming from the country it operates. Therefore, we assume that this is not the case but acknowledge that our IV exogeneity depends on this.

In the first stage, we regress the company's change in emission score (T-1 to T) on our IV, country-year-delta variable, representing the one-year change in country-mean.<sup>8</sup> Next, we estimate an OLS regression using the fitted values of change in emission score from the first stage regression as the independent variable and the company's CARs as our dependent variable. This procedure gives us the effect that a firm's change in emission score has on their CAR but through the country-year mean variable. We test for relevance using an F-test, and the result is displayed in Table 7. Our F-statistic of 6.55 is below the general accepted cut-off level of 10. However, we still run the IV regression to see if it changes our result, but we will be cautious with the interpretation given the weak instrument.

Table 7 - IV: F-Test

Model	Hypothesis 2a and 2b
F-statistic	6.55

<sup>&</sup>lt;sup>8</sup> We tried using the company's change in emission score from T to T+1, but the variable got an F-score of 0.0001 making it inadequate as an instrument.

## 6. Results

#### 6.1 Hypothesis 1a) Firms use M&As to improve their emission risk

Through our difference-in-difference regression, both with and without a propensity scorematched control group, we find evidence that companies who performed an M&A see a deterioration in their emission score. The results indicate that improving emission risk is not the primary focus when doing an M&A.

In the difference-in-difference regression, the treatment companies see a statistically significant decrease in emission score at the 1% level post-M&A. In specification one in Table 9, our group of acquirers, on average, see a -5.04 (-12.44%) lower emission score in the period after the M&A (t to t+2) than what they would have seen if they had not performed the M&A. The negative effect post-M&A is also found when using propensity score matching to form a control group (specification 3). Our treatment group, on average, sees a -3.32 (-5.47%) lower emission score in the period after the M&A, and this is statistically significant at the 1% level. These findings contradict our hypothesis that firms use M&A to improve their emission risk. Our OLS did not find any significant results when only using M&A as the treatment, and the regression output is listed in Table 8.

The sample of M&A firms sees a statically significant lower emission score than non-M&A firms and is the opposite of what we hypostatized. A potential reason why our treatment firms are seeing a lower emission score after the M&A is that the motivation of the transaction was rooted in operational and financial synergies rather than improving its environmental profile. As Gaughan (2017) explains, the primary motive for doing an M&A is to create value through such synergies, potentially making environmental risk secondary. With environmental risk not being incorporated in the decision-making, acquirers are increasing the risk of acquiring firms with poor environmental governance increasing their own emission risk.

The complexity of performing an M&A and the relatively high chance of completing unsuccessful acquisitions can explain why acquirers, on average, see a deterioration in their emission score post-M&A. Many M&As experience issues related to high complexity and poor post-merger integration resulting in lower returns and more unsatisfactory operational performance. Such problems arising from the M&A can hinder a firm from appropriately adapting and implementing new environmental strategies, resulting in a lower improvement

in emission score than what they could have achieved without the M&A. Moreover, we argue that focusing on post-merger integration and solving other complex tasks related to the transaction can diminish the learning effect that Aktas et al. (2011) and Malik (2014) find as it is given less attention. Hence, the complexity arising from the M&A can reduce the improvement in a firm's environmental profile.

While the change in direction is not what we expected, there is a significant change in their emission score. That firms can see a change in emission score after an M&A is in line with Gaughan (2017), who says that M&A changes the company's organizational structure and that M&A can change a firm's business profile. Moreover, acquisitions are usually significant investments for a firm. If the acquirer and the target have a different environmental profile, it would be reasonable that the post-acquisition firm should see a change in its environmental profile.

Specifications one and three in Table 9 find that all companies, on average, see an improvement in their emission score in the period after the M&A (T to T+2), suggesting there is an overall increase in emission scores. As all companies see an improvement in emission score and the Treatment x Post M&A term is negative, the results suggest there are more effective ways to improve the emission score than M&As. While it is challenging to identify what investments firms have taken to see this change in emission score, it would be reasonable to assume that firms must have taken some action to change their operation to see this result. These investments can have been more directly and accurately targeted to change a firm's environmental profile than an M&A, which often focuses on achieving operational or financial synergies (Gaughan, 2017, p. 125 - 177; Lewis & McKone, 2016). Moreover, non-acquiring firms can potentially focus on improving and implementing these investments or initiatives without the complexity and other challenges that arise after an M&A.

## **6.2 Hypothesis 1b)** The change in acquirers emission score is positively correlated with the relative difference in emission score between the target and the acquirer

When using the relative difference between the acquirer and targets emission score as continuous treatment, we find that firms can use M&A to improve their emission score when incorporating it into their decision-making. This finding is consistent through our OLS and difference-in-differences, both with and without a propensity score-matched control group.

From the OLS, we find that the relative difference in emission score in T-1 significantly affects the acquirers' emission score both in T and T+1 and is illustrated in specifications 3 and 4 in Table 8. A one standard deviation increase in the relative difference in emission score between the acquirer and the target leads to an 0.66 increase in emission score for the acquirer in T and a 0.53 increase in T+1.

The more robust difference-in-difference estimator, which reduces the risk of endogeneity, adds further support to the finding from the OLS, allowing for a more casual interpretation. From regression 2 in Table 9, where the control group consists of all non-M&A firms from the Refinitiv universe, we see that  $\frac{TARGET}{ACQ}ES \times Post M$ &A, has a significant positive effect on the acquirer's emission score. When using a more nuanced propensity-matched control group, we find  $\frac{TARGET}{ACQ}ES \times Post M$ &A to be smaller but equally significant. This can be found in specification 4 in Table 9. In terms of significance, a one standard deviation increase in the relative difference in emission score between the acquirer and the target leads to an 0.53 and 1.01 increase in the acquirer's emission score, using the respective control groups.

These results suggest that acquirers can integrate and learn from the target's environmental practice to improve their environmental profile and reduce the associated risk, supporting the findings of Aktas et al. (2011) and Tampakoudis and Anagnostopoulou (2020). In the OLS, we find the effect to be larger and more significant in T+1. This can be because it takes time to realize synergies, transfer knowledge, and smoothly integrate the two firms, resulting in a lag effect on the emission risk. Moreover, the acquirer focusing on more financially important and time-sensitive issues related to the post-merger integration in year T can affect the learning effect related to environmental practice. Consequently, one would expect the learning effect to be more evident after addressing these issues. Lastly, we argue that the lagged effect on the

emission score can come from it taking longer to see the results from sustainable investments (Kwon et al., 2018).

The effect on acquires emission score in both T and T+1 differs from Barros and Verga Matos et al. (2021), who only find an impact on the acquirers' emission score in T+1. A potential cause for this difference can be that we require the target to have an emission score. The target's emission score can reduce the information asymmetry between the two parts, making it easier for the acquirer to assess the target's environmental capabilities. This can reduce the risk of the transaction, allowing for smoother integration and spending more time realizing synergies, resulting in an enhanced learning effect.

Moreover, targets with an emission score are more likely to be more ESG and CSR aware and transparent in their reporting. This awareness and transparency can smooth the integrations process, allowing for better sharing of knowledge and culture, resulting in a more synergetic transaction. Consequently, one could expect a more immediate effect on the acquirers' emission score when the target also has an emission score.

Our difference-in-differences with different control groups further support that acquirers can learn from firms with a better emission performance to improve their own emission risk. Using a pre and post-M&A period of three years, we find that the emission score improvement is long-lasting. In combination with finding a larger and more significant effect in T+1 than T, the result from the difference-in-difference can indicate that investments in sustainability take longer to materialize.

However, the statistical significance of  $\frac{TARGET}{ACO}ES \times Post M$ &A, is lower in the difference-indifference than in our OLS when measuring the effect in T+1, suggesting our OLS suffers from endogeneity. While being significant at the 5% level in the OLS, it is only significant at the 10% level in our difference-in-difference. Moreover, when mimicking randomization and control creating a more nuanced group using propensity score matching,  $\frac{TARGET}{ACO}$  ES x Post M&A is lower in magnitude but equally significant. The reduction in magnitude can suggest that our larger control group suffers from endogeneity. This can come from our treatment companies being different from our control group.

However, we find the relative difference in emission scores statistically significant. This is consistent when correcting for endogeneity using a difference-in-difference with a general and

propensity scored control group. The robustness of the difference-in-differences with varying control groups, combined with our findings in the OLS, allows for a more casual interpretation of our results.

The result in the difference-in-difference using a continuous treatment differs from the results when only using M&A as treatment. The more nuanced treatment allows us to understand better what drives the change in emission risk after an M&A, as it enables us to measure the degree of treatment the acquiring firms receive. Moreover, the inclusion of a continuous treatment allows us to say something about the motivation of the transaction, and the changing results suggest that acquirers need to evaluate the environmental profile of the target to improve their own emission risk. These results give corporations and managers insight into how they can enhance a firm's environmental risk. If done correctly, M&A can be a way to go about it.

Lastly, the target's emission score can make it easier for Refinitiv to assess the impact of the transaction on the acquirer's emission score. By analyzing the target's performance within the parameters included in the emission score, they can include this when determining the acquirer score. If the target has an emission score, this can more easily be incorporated already in year T due to better disclosure of information (Refinitiv, 2021). However, the more significant effect in year T+1 suggests an additional learning effect, as previously discussed.

To summarize, we find a mixed effect of doing M&As on the acquirers' emission score. When not including the targets' environmental capabilities in the decision-making, we find evidence that M&As worsen the acquirers' environmental risk. We argue that this effect comes from the lack of attention given to environmental issues and the overall complexity when integrating a new firm, leading to improving its environmental risk becoming secondary. However, when incorporating the environmental aspect to the transaction, we find that firms can use M&A to reduce their environmental risk. Our results indicate a positive correlation between the relative difference in emission score on the acquirers' emission score change. We assert this finding that these transactions are more synergistic, less risky, and have lower information asymmetry. These factors allow for an enhanced learning effect and knowledge transfer, resulting in a reduced environmental risk for the acquirer.

	Dependant Variable					
_	ΔES	ΔES	ΔES	ΔES		
	T-1 to T	T to T+1	T-1 to T	T to T+1		
	(1)	(2)	(3)	(4)		
M&A	-1.005 (0.693)	-0.786 (0.679)				
$\frac{TARGET}{ACQ}ES$			3.835 <sup>*</sup> (1.990)	4.079 <sup>**</sup> (2.078)		
Relative Deal Size	5.144 <sup>*</sup> (2.931)	-2.646 (2.756)	4.444 <sup>*</sup> (2.339)	0.287 (2.323)		
Ln (Size)	0.024 (0.249)	-0.005 (0.249)	-0.482 (0.356)	-0.460 (0.357)		
Leverage	-0.087 (1.907)	0.199 (1.910)	-3.595 (3.375)	-3.021 (3.388)		
P/B	-0.005 (0.004)	-0.005 (0.004)	0.223 <sup>**</sup> (0.097)	0.221 <sup>**</sup> (0.097)		
R&D/Assets	12.256 <sup>**</sup> (5.907)	12.068 <sup>**</sup> (5.910)	-10.815 (11.783)	-11.562 (11.804)		
Capex/Assets	-4.736 (8.461)	-5.917 (8.487)	-3.610 (11.815)	-4.776 (11.835)		
Constant	-1.158 (6.444)	-0.622 (6.436)	20.497 <sup>**</sup> (9.109)	20.096 <sup>**</sup> (9.126)		
Payment Fixed Effects	No	No	No	No		
Country Fixed Effects	Yes	Yes	Yes	Yes		
Industry Fixed Effects	No	No	No	No		
Time Fixed Effects	Yes	Yes	Yes	Yes		
Observations	2,622	2,622	886	886		
$R^2$	0.041	0.04	0.066	0.063		
Adjusted R <sup>2</sup>	0.023	0.022	0.023	0.02		

 Table 8 - OLS analysis of M&As effect on emission scores

#### Table 9 - Difference-in-difference analysis of M&As effect on emission scores.

Estimators 1 and 2 use a broader control group, while estimators 3 and 4 use a propensity score-matched control group. Because we use a fixed effect difference-in-difference model, the treatment variable will not appear as an individual coefficient as the variable has no variation.

	Dependant Variable						
	Emission score						
	(1)	(2)	(3)	(4)			
Treatment x Post M&A	-5.041***		-3.325***				
	(0.769)		(1.067)				
$\frac{TARGET}{ACO} ES \times Post M \& A$		2.286 <sup>*</sup>		1.844 <sup>*</sup>			
ACQ ES x Post M&A		(1.312)		(1.050)			
Post M&A	10.006***	9.853***	7.792***	6.921***			
	(0.372)	(0.362)	(0.749)	(1.117)			
Ln (Size)	8.214***	7.487***	10.063***	4.584 <sup>*</sup>			
, ,	(0.695)	(0.736)	(1.253)	(2.344)			
Leverage	-1.162	-0.903	-2.550	2.099			
0	(2.089)	(2.193)	(4.108)	(7.447)			
Р/В	-0.0001	-0.00004	-0.001	-0.003			
	(0.001)	(0.001)	(0.003)	(0.003)			
R&D/Assets	24.532**	19.895 <sup>*</sup>	30.985 <sup>*</sup>	15.524			
	(12.028)	(12.041)	(17.419)	(53.414)			
Capex/Assets	-1.316***	-1.297***	-2.030****	-2.103***			
	(0.147)	(0.126)	(0.076)	(0.057)			
Observations	17,030	14,425	5,789	1,292			
Firm-Specific Fixed Effects	Yes	Yes	Yes	Yes			
Time Fixed Effects	Yes	Yes	Yes	Yes			
Note			*p<0.1; **p<0	.05; ***p<0.01			

**6.3 Hypothesis 2a)** Companies improving their emission score through M&A when it is material in the acquirer's industry, will see abnormal short-term returns.

# **6.4 Hypothesis 2b)** Companies improving their emissions score through M&A when it is material in the acquirer's industry, will see abnormal long-term returns.

We are unable to establish a relationship between short-term returns and change in environmental risk when accounting for industry materiality. The missing relationship is consistent through the OLS and difference-in-difference, both with and without a propensity score-matched control group. The OLS results are presented in Table 10, while the results from our difference-in-differences are presented in Table 11 and Table 12. Furthermore, we do not find a relationship between long-term returns and change in environmental risk when accounting for industry materiality. This result is presented in Table 10.

With a missing relationship between improving emission risk, industry materiality, and shortterm returns, we fail to reject the null hypothesis. While we cannot draw any conclusions, it is worth discussing why we might get the results as the theories relating returns to environmental investments are conflicting.

Because a lower emission risk reduces the consequences of future environmental regulations and punitive actions, we expected firms that improved their emission risk through M&A to see positive abnormal announcement returns. This effect should be amplified when emissions represent a material risk in the industry, as there is a higher chance of regulatory changes, making it more important and resulting in more significant consequences.

Moreover, the reduced environmental risk reduces a firm's systematic risk and cost of capital, and banks favor environmentally-friendly firms. This can improve a firm's access to capital, allowing them to undertake value-enhancing projects, further speaking for positive announcement returns (Eliwa et al., 2021; Houston & Shan, 2019). However, our results do not find such a relationship, suggesting investors do not find a reduction in environmental risk to be value-enhancing.

Our results do not find evidence of a carbon premium which speaks for lower abnormal returns. Following finance theory, the reduced carbon premium should lead to lower returns as firm risk is reduced (Bolton & Kacperczyk, 2021). The effect of the carbon premium can have been offset by the theory that speaks for positive abnormal returns. Hence, the conflicting

theories surrounding emission risk and returns can explain why we cannot find any significant effect.

We can still not establish a relationship between emission risk, short and long-term returns, and industry materiality when including the relative difference in emission score. The relative difference is accessible to investors on the announcement day and can be easier to incorporate when evaluating the transaction. While transactions where the target has an emission score, can reduce the information symmetry, resulting in lower risk, smoother integration, and more synergies, our result suggests that this does not translate to abnormal returns (Aktas et al., 2011; Malik, 2014). We attribute the missing relationship to the conflicting evidence regarding environmental investments and returns discussed above.

Our OLS cannot establish any connection between the acquirers' emission score, materiality, and long-term returns. The lack of connection is consistent with various intervals of change in emission score and the relative difference in emission score. We hypothesized that the change in emission score would affect long-term returns because investments directed towards sustainability take longer to materialize, and the market has more difficulties pricing long-term oriented environmental investments.

Moreover, the missing relationship between changing emission risk and long-term returns can be caused by other events in the 36 months estimation period. The 36-month period after the transaction allows us to explore if the environmental investment was sound and materialized. However, there is a trade-off when measuring long-term returns. While the M&A can have created value for the acquirer, there can have been other corporate events in this period affecting their return. This makes it challenging to isolate the effect of a changing emission risk resulting from the M&A on acquirer returns.

To conclude, we did not find a relationship between emission risk and returns when accounting for materiality. We performed a long-term return analysis to account for the lagged effect of investing in sustainability. The short-term returns were tested extensively; however, neither the OLS nor the difference-in-differences found significant results. Without statistically significant results, it is hard to draw firm conclusions about the relationship between changing emission risk through M&A and adjacent returns.

-2 to +2 CAR			LT Returns		
(1)	(2)	(3)	(4)	(5)	(6)
-0.001	. ,	. ,	-0.027	. ,	. ,
(0.025)			(0.298)		
	0.013			0.426	
	(0.028)			(0.344)	
		-1.513			13.122
		(1.137)			(9.696)
0.021					
			(0.170)		
(0.013)				0.299	
	0.003				
	(0.016)				
		0.372			-10.479
		(0.914)			(7.918)
-0.647	-0.612	-0.958	-7.697	-6.636	-26.793
(0.406)	(0.410)	(1.176)	(5.016)	(5.013)	(10.308)
0.001	-0.018	0.475	-3.726	-3.113	-0.909
(0.190)	(0.189)	(0.616)	(2.539)	(2.522)	(6.625)
2.384**	2.392**	0.577	16.349	18.095	84.824
(1.146)	(1.149)	(3.533)	(14.685)	(14.656)	(37.515)
-0.0003	-0.001	0.012	0.048	0.060	-0.196
(0.015)	(0.015)	(0.012	(0.262)	(0.261)	(0.304)
					*
					662.228 <sup>*</sup> (198.067
(0.207)	(01200)	(10:000)	(001107)	(001202)	(1501007
-1.686	-1.663	-6.668	49.520**	51.585**	312.832 <sup>*</sup>
(1.800)	(1.804)	(7.355)	(24.250)	(24.189)	(71.278)
-0.072	-0.071	0.880	-1.485	-1.453	-4.164
(0.083)	(0.084)	(0.823)	(0.940)	(0.937)	(6.903)
0.0001	0.003		-0.107	-0.210***	
(0.007)	(0.007)		(0.086)	(0.083)	
-0.083	-0.084	-0.133	1.758	1.620	1.192
(0.164)	(0.164)	(0.503)	(2.091)	(2.080)	(4.576)
0.090	0.098	0.408	1.693	2.044	9.712
(0.340)	(0.341)	(1.109)	(4.182)	(4.176)	(10.040)
-0.044	-0.082	0.539	-2.730	-3.429	15.371
(0.438)	(0.438)	(1.563)	(5.296)	(5.292)	(14.272)
-0.330	-0.096	-13.664	109.654***	101.229**	-127.568
(3.221)	(3.221)	(13.122)	(40.799)	(40.591)	(117.094
Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	No	Yes	Yes	No
	No	No	No	No	No
					Yes 182
					0.356
0.1+3	0.140	-0.016	0.266	0.270	0.550
	(0.025) 0.021 (0.015) -0.647 (0.406) 0.001 (0.190) 2.384** (1.146) -0.0003 (0.015) 0.190 (5.157) -1.686 (1.800) -0.072 (0.083) 0.0001 (0.007) -1.686 (1.800) -0.072 (0.083) 0.0001 (0.007) -0.083 (0.164) 0.090 (0.340) -0.044 (0.438) -0.330 (3.221) Yes	(1)         (2)           -0.001         0.025)           0.021         0.028)           0.021         0.003           (0.015)         0.003           0.016)         0.016)           -0.647         -0.612           (0.406)         (0.410)           0.001         -0.018           (0.190)         (0.189)           2.384**         2.392**           (1.146)         (1.149)           -0.0003         -0.001           (0.015)         (0.015)           0.190         -0.216           (5.157)         (5.160)           -1.686         -1.663           (1.800)         (1.804)           -0.072         -0.071           (0.083)         (0.084)           0.0001         0.003           (0.007)         (0.007)           -0.083         -0.084           (0.164)         (0.164)           0.090         0.098           (0.340)         (0.341)           -0.030         -0.096           (3.221)         (3.221)           Yes         Yes           No         No           Yes	(1)         (2)         (3)           -0.001 (0.025)         -0.013 (0.028)         -1.513 (1.137)           0.021 (0.015)         -1.513 (1.137)         -1.513 (1.137)           0.021 (0.015)         0.003 (0.016)         0.372 (0.914)           -0.647         -0.612         -0.958 (0.406)         0.410)           -0.001         -0.018         0.475 (0.190)         0.616)           2.384**         2.392**         0.577 (1.146)         0.012 (0.015)           2.384**         2.392**         0.577 (1.146)         0.012 (0.015)           0.003         -0.001         0.012 (0.015)         0.027)           0.190         -0.216         -8.261 (5.157)         (5.160)           0.190         -0.216         -8.261 (5.157)         (5.160)           0.190         -0.216         -8.261 (5.189)         (0.823)           -1.686         -1.663         -6.668 (1.800)         (1.804)         (7.355)           -0.072         -0.071         0.880 (0.083)         (0.083)         (0.823)           0.0001         0.003 (0.007)         (0.007)         (0.503)         (0.503)           0.090         0.988         0.408         (0.503)           0.090         0.098 <t< td=""><td>(1)         (2)         (3)         (4)           -0.001         -0.027         (0.298)         -0.027           (0.025)         0.013         (0.298)         -0.255           0.021         (0.025)         -1.513         (1.137)           0.021         0.013         (0.170)         -0.265           0.021         0.013         (0.170)         -0.265           0.014         -0.512         -0.958         -7.697           (0.406)         (0.410)         (1.176)         (5.016)           0.001         -0.018         0.475         -3.726           (0.190)         (0.189)         (0.616)         (2.539)           2.384**         2.392**         0.577         16.349           (1.146)         (1.149)         (3.533)         (14.685)           -0.0003         -0.001         0.012         0.048           (0.015)         (0.027)         (0.262)         0.490           (5.157)         (5.160)         (18.990)         (69.497)           -1.686         -1.663         -6.668         49.520*           (1.800)         (1.804)         (7.355)         (24.250)           -0.072         -0.071         0.880&lt;</td><td><math display="block">\begin{array}{ c c c c c c c c c c c c c c c c c c c</math></td></t<>	(1)         (2)         (3)         (4)           -0.001         -0.027         (0.298)         -0.027           (0.025)         0.013         (0.298)         -0.255           0.021         (0.025)         -1.513         (1.137)           0.021         0.013         (0.170)         -0.265           0.021         0.013         (0.170)         -0.265           0.014         -0.512         -0.958         -7.697           (0.406)         (0.410)         (1.176)         (5.016)           0.001         -0.018         0.475         -3.726           (0.190)         (0.189)         (0.616)         (2.539)           2.384**         2.392**         0.577         16.349           (1.146)         (1.149)         (3.533)         (14.685)           -0.0003         -0.001         0.012         0.048           (0.015)         (0.027)         (0.262)         0.490           (5.157)         (5.160)         (18.990)         (69.497)           -1.686         -1.663         -6.668         49.520*           (1.800)         (1.804)         (7.355)         (24.250)           -0.072         -0.071         0.880<	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$

# **Table 10** – OLS regressions measuring the effect of a change in emission score onacquirer returns

#### Table 11 – Difference-in-difference regressions, measuring the effect of a change in emission score on acquirer returns.

Because we use a fixed effect difference-in-difference model, the industry materiality and change in emission score variable will not appear as an individual coefficient as the variable has no variation. Specifications 1, 2, and 3 are without propensity score matching, while specifications 4, 5, and 6 use propensity score matching.

	AR					
	(1)	(2)	(3)	(4)	(5)	(6)
( $\Delta$ ES T-1 to T) x Industry Materiality x Post M&A	0.011 (0.008)			-0.016 (0.027)		
( $\Delta$ ES T to T+1) x Industry Materiality x Post M&A		-0.001 (0.007)			0.067 (0.044)	
$\frac{TARGET}{ACQ}ES \times \text{Industry Materiality x Post M&A}$		(0.007)	-0.389 (0.289)	0.014	(0.044)	-0.169 (0.492)
( $\Delta$ ES T-1 to T) x Post M&A	0.0002 (0.004)			(0.015)		
(Δ ES T to T+1) x Post M&A		0.002 (0.004)			-0.034 (0.039)	
$\frac{TARGET}{ACQ}ES \ge N \text{ Post M&A}$			0.228 (0.234)			0.010 (0.460)
Industry Materiality x Post M&A	-0.133 (0.097)	-0.174 <sup>*</sup> (0.098)	-0.155 (0.415)	-0.112 (0.422)	0.150 (0.447)	-0.140 (0.422)
Post M&A	-0.205 (0.173)	-0.197 (0.174)	1.115 <sup>*</sup> (0.612)	1.293 <sup>**</sup> (0.632)	0.900 (0.605)	1.072 <sup>*</sup> (0.623)
Observations	11,690	11,690	11,690	2,030	2,030	2,030
Firm-Specific Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Note				*p<0.1	; **p<0.05;	***p<0.01

#### Table 12 – Quadruple difference-in-difference

	Dependant Variable			
		AR		
	(1)	(2)	(3)	
(Δ ES T-1 to T) x Treatment	0.008			
x Industry Materiality x Post M&A	(0.017)			
(Δ ES T to T+1) x Treatment		0.002		
x Industry Materiality x Post M&A		(0.019)		
TARGET			-0.214	
$\frac{1}{ACQ}$ ES x Industry Materiality x Post M&A			(0.733)	
Industry Materiality x Treatment x Post M&A	0.078	0.097	0.085	
ndustry Materianty x Treatment x Post M&A	(0.274)	(0.276)	(0.504)	
Tura tura anta a Dia at N40 A	0.015	-0.027	0.158	
Treatment x Post M&A	(0.156)	(0.152)	(0.294)	
	0.071	0.076	0.052	
ndustry Materiality x Post M&A	(0.181)	(0.180)	(0.232)	
	0.364	0.396	0.286	
Post M&A	(0.446)	(0.451)	(0.666)	
Observations	5,159	5,159	3,019	
Firm-Specific Fixed Effects	Yes	Yes	Yes	
Time Fixed Effects	Yes	Yes	Yes	

Because we use a fixed effect difference-in-difference model, the industry materiality, treatment, and change in emission score variable will not appear as an individual coefficient as the variable has no variation.

# 7. Robustness

# 7.1 Result of Instrumental Variable

The results from the instrumental variable (IV) regression are found in Table 13. In specification one, we regress the company's change in emission score (T-1 to T) on our IV, country-year-delta variable. The fitted values found are used in a Two-Stage Least Squares regression (2SLS) trying to explain short, and long-term returns and are presented in specifications 2 and 3.

Our instrumental variable interacted with industry materiality does not find any significant effect on either acquirer's short or long-term returns and is consistent with our findings in hypotheses 2a and 2b. This can suggest that our original variable of interest,  $\Delta ES \times M$ , does not suffer from endogeneity issues related to omitted variable bias or reverse causality. However, the predicted variable ( $\Delta ES0$ ) in regression 3 is significant at the 10% level when explaining acquirers' long-term returns. This differs from our finding in hypothesis 2b, where  $\Delta ES$  had no statistical significance. While  $\Delta ES$  as an individual variable is not our primary variable of interest, the change in significance makes it ambiguous whether our model suffers from endogeneity. A potential cause that can create such an endogeneity is a correlation between a firm's voluntary environmental disclosure and its financial performance. However, the effect of 'his potential bias is inconclusive and is discussed in 46ethodlogy section.

Based on the results above, we cannot rule out that our models measuring the effect of change in emission score on returns suffer from endogeneity. However, the primary variable of interest,  $\Delta ES \ x \ Materiality$ , remains consistent throughout our regressions, suggesting that endogeneity is insignificant. Moreover, drawing any conclusion from the IV rest on the assumption that our IV is exogenous. If our IV does not meet this criterion, the result from the IV regression can also be inconsistent.

Table 13 – Instrumental Variable Regression

## 7.2 Other Robustness Test

We rerun the regressions only using transactions after the Paris agreement in 2015 to see if there has been a change in investor awareness. This robustness test is done for the OLS regressions that measure how a change in emission score affects short and long-term returns. The results are presented in Table 14.

Our result suggests that the one-year change in emission score from T to T+1 affects the acquirers' long-term returns. The one-year change in emission score from T to T+1 is significant at the 10% level, and a one standard deviation increase leads to 3,68% higher monthly returns. However, we find no significant effect when interacting the coefficient with industry materiality. This suggests that the materiality of emission-related issues does not impact acquirers' long-term returns.

This result differs from our original OLS, where we did not account for the period before and after the Paris agreement. The moderate effect of an improving emission risk and long-term return can suggest there can have been a change in investor awareness after the Paris agreement. A potential reason for this can be that the Paris agreement was a significant event, being a legally binding agreement between 193 countries to limit global warming (United Nations, 2015). The ratification of the Paris agreement gave clarity to banks, investors, and other stakeholders that regulatory changes combating climate change would come. Consequently, banks started incorporating emission risk in their decision-making, reducing their exposure to high polluting firms and increasing their credit spreads (Delis et al., 2019; Seltzer et al., 2020).

An improving emission score positively affects long-term returns and can come from a reduced risk of regulatory changes, punitive actions, and lower systematic risk (Giese et al., 2015; Lodh, 2020; Ng & Rezaee, 2015). Being better suited to withstand regulatory changes and avoid punitive action will help firms protect their future profitability leading to higher valuations. Moreover, the lower systematic risk can reduce their cost of capital, leading to a higher firm value. The threats of such changes have increased after the Paris agreement and might have raised awareness among investors. This can explain why we now see an effect of reduced emission risk on acquirer returns,

Finding a relationship between changing emission scores and long-term returns can suggest that investments in improving sustainability take longer to materialize. As Krüger (2015)

discusses, investors tend to sell off when firms announce environmental investments, even if they might be value-enhancing. This can be because it reduces short-term cash flow, and they fear executives are making green investments to improve their reputation at the cost of the shareholders. However, when these environmental investments start to yield their returns, investors might incorporate this value resulting in higher returns.

We only find a positive effect on return using the acquirers' change in emission score from T to T+1. The same period in which we saw M&A have the most significant effect on acquirers' emission scores in hypothesis one. A potential reason for this is that as the reduced emission risk from the M&A becomes more evident, it is easier for investors to assess the benefits of the investment, resulting in higher equity returns.

-		LT Returns		Transactions After Paris Agreement			
	(1)	(2)	(3)	(4)	(5)	(6)	
ESO x Materiality	-0.027	(=)	(0)	0.519	(0)	(0)	
T-1 to T)	(0.298)			(0.442)			
ES1 x Materiality		0.426			-0.303		
T to T+1)		(0.344)			(0.633)		
$\frac{ARGET}{ACQ}ES \times Materiality$			13.122 (9.696)			16.224 (11.034)	
1ESO	-0.265			-0.360			
T-1 to T)	(0.170)			(0.280)			
AES1		0.299			0.584*		
T to T+1)		(0.197)			(0.333)		
$\frac{CARGET}{ACQ}ES$			-10.479			-8.223	
ACQ			(7.918)			(8.853)	
Materiality	-7.697	-6.636	-26.793**	-2.753	-5.305	-32.744***	
	(5.016)	(5.013)	(10.308)	(6.917)	(7.012)	(14.252)	
n (Size)	-3.726	-3.113	-0.909	-1.222	-0.676	5.138	
	(2.539)	(2.522)	(6.625)	(3.334)	(3.306)	(7.108)	
Leverage	16.349	18.095	84.824**	-0.184	2.958	71.376	
-	(14.685)	(14.656)	(37.515)	(19.717)	(19.579)	(44.291)	
Р/В	0.048	0.060	-0.196	0.185	0.165	0.003	
	(0.262)	(0.261)	(0.304)	(0.268)	(0.267)	(2.365)	
&D/Assets	94.940	110.019	662.228***	255.466****	278.829***	710.733****	
	(69.497)	(69.292)	(198.067)	(88.719)	(87.909)	(238.253)	
Profitability	49.520**	51.585**	312.832****	41.800	48.748	101.235	
,	(24.250)	(24.189)	(71.278)	(45.629)	(45.383)	(129.581)	
ACQ 2 Year Growth	-1.485	-1.453	-4.164	1.049	1.025	-1.521	
	(0.940)	(0.937)	(6.903)	(1.945)	(1.941)	(7.598)	
ACQ Emission score, T-1	-0.107	-0.210***		-0.072	-0.153		
	(0.086)	(0.083)		(0.118)	(0.116)		
_n (Cash)	1.758	1.620	1.192	0.570	0.393	-3.099	
	(2.091)	(2.080)	(4.576)	(2.677)	(2.663)	(5.731)	
ndustry Related	1.693	2.044	9.712	9.483	9.451	0.081	
,	(4.182)	(4.176)	(10.040)	(6.003)	(5.987)	(13.112)	
Relative Deal Size	-2.730	-3.429	15.371	-2.166	-2.407	13.385	
	(5.296)	(5.292)	(14.272)	(6.205)	(6.189)	(16.136)	
Constant	109.654***	101.229**	-127.568	-12.412	-15.051	-69.601	
	(40.799)	(40.591)	(117.094)	(54.492)	(54.307)	(118.231)	
Payment Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	
ndustry Fixed Effects	No	No	No	No	No	No	
Time Fixed Effects	Yes	Yes	Yes	No	No	No	
Observations	936	936	182	358	358	92	
$\mathbb{R}^2$	0.326	0.329	0.356	0.317	0.320	0.251	
Adjusted R <sup>2</sup>	0.266	0.270	0.202	0.216	0.219	0.103	

# **Table 14** - OLS measuring the impact of a change in emissions score on long-termreturns only using transactions after the Paris agreement

# 8. Limitations and further research

To make our contribution regarding how emissions affect M&As more nuanced, we will reflect on this study's limitations. Throughout this paper, we have had to decide what data providers to use, which variables to use, which methodology to use and what econometrically test to perform. While we have discussed both pros, cons, and limitations with the decisions made, the choices can have affected the result. We will summarize the caveats and limitations of these decisions below, and from this, we will suggest avenues for further research.

# 8.1 Limitations

One of the main limitations is the limited number of transactions researched. When only requiring the acquirer to have an emissions score, we have 1,169 transactions, but we have only 206 transactions when requiring both parties to be scored. The limited number of transactions will improve with time as more transactions where both the acquirer and the target have an emission score will occur. Another potential solution to increasing the number of transactions could have been to choose another ESG/emissions score provider. While we ought to believe that Refinitiv was the appropriate vendor of emission scores, it could be that Bloomberg, MSCI, or another provider would have better coverage for the companies in our initial M&A sample.

Refinitiv's ESG score, and subscores that make up the different pillars, are based on relative rating. This results in firms that score marginally better than average could obtain a better score than comparable firms. Because specific components of these scores are country and industry-dependent, this could skew our results. The country and industry dependency of the scores put further suspicion on the endogeneity of our instrumental variable. Moreover, Refinitiv requires a certain level of disclosure to score companies. Consequently, our sample can be biased as scored companies might be more environmental-focused and not represent the market average.

The lack of convergence among the different ESG/emission score providers makes casual interpretations more difficult. If we were to use another provider, we could have gotten another result because the various providers give firms different scores. Moreover, they cover different companies, which would result in a different sample. The different samples and scoring could

result in significantly different results, making it difficult to interpret our findings as definitive. However, we minimize this error by using the emission score, a quantitative and specific pillar, leaving less room for subjective assessment,

We elaborated on the difficulties of measuring long-term abnormal returns, and great researchers such as Jay Ritter and Eugene Fama still disagree on what method yields the most accurate results. When creating the benchmark measuring long-term returns, the difference in methodology between the Jensen-alpha and the BAHR approach can yield different results. The divergence among the models and using a mix of region and country-specific five-factor Fama-French models makes it difficult to say something conclusive about our long-term results.

Lastly, researching M&A is inherently difficult due to the self-selection problem. M&As are not randomly assigned; it is a choice the acquirer makes. Targets are also characterized by certain traits, making the probability of targets receiving bids non-random. This can create a selection bias. These inherent problems make it harder to interpret our results casually.

# 8.2 Further research

Based upon the limitation of the study and other ideas that would complement or take our study further, we will propose avenues for further research.

To repeat this study later would yield a larger sample size and could be an interesting exercise and hopefully improve the robustness of our research. Further, as Refinitiv's coverage improves, companies' CO2 emissions and capital expenditures related to environmental investments should be better covered. To add such granular data could improve our understanding of what part of the targets emission profile acquirer find attractive and how investors value it. Additionally, as companies improve their emission-related reporting, it would be interesting to break its emission down to scope 1, scope 2, and scope 3 and see how this affects acquirer decisions. Lastly, to repeat the study and incorporate the potential extensions above, using a different ESG data provider could deepen our understanding of how corporate emissions affect M&As.

# 9. Conclusion

This thesis explores if companies use or can use M&A to reduce their environmental risk and how this affects their returns when accounting for the industry materiality of environmental issues. We have identified two different relationships between M&A and acquirers' emission risk and found a partial relationship between changing emission risk and returns.

We found that M&A, on average, decreases the acquirers' emission score when comparing their performance to different control groups. The results indicate that improving emission risk is not the primary focus when doing an M&A and that other more directly targeted investments might be better suited to reduce emission risk.

However, when using the relative difference between the acquirer and targets emission score as continuous treatment, we find that firms can use M&A to improve their emission score when incorporating it into their decision-making. We argue that this can come from the motivation of the transaction. By evaluating and acquiring a target with a better emission score than itself, the transaction can be "green" motivated, which results in an improved emission score of the acquirer. We further argue that this can come from these transactions being less risky and having lower information asymmetry, leading to an enhanced learning effect and transfer of environmental knowledge between the target and acquirer.

We establish a positive relationship between a changing emission score and acquirers' longterm returns when only looking at transactions completed after the announcement of the Paris agreement in 2015. This finding differs from when we used the entire sample of transactions; then, we found no relationship between changing emission scores and acquirers' long-term returns. We attribute this result to increased investor awareness as the ratification of the Paris agreement clarified to banks, investors, and other stakeholders that regulatory changes combating climate change would come. However, accounting for the industry materiality of GHG emissions does not have a statistically significant effect on short or long-term returns, suggesting that investors are not aware of or do not value the industry materiality of the issue. This was consistent using the entire sample and when only evaluating transactions made after the Paris agreement.

When using the entire sample of transactions, we find no relationship between a change in emission score and short and long-term returns after accounting for materiality. We attribute the missing relationship to the conflicting environmental investments and returns theories. Evidence suggests that reduced emission risk will lead to a lower cost of capital and higher future cash flow as one is less prone to future punitive regulation, resulting in higher firm value. However, fundamental finance theory says that lower risk results in lower returns speaking for lower future returns.

This thesis also has some managerial implications. With increasing pressure on firms to become more sustainable and comply with stricter environmental regulations and financial reporting, managers will have to take action. With an effect on emission score the same year and one year after the transaction, M&A offers a relatively quick avenue to comply. The results add insight into how firms can use M&A to manage their emission risk and compel with new legislation and how the market will react to such transactions.

# 10. References

- Aktas, N., de Bodt, E., & Cousin, J. G. (2011). Do financial markets care about SRI? Evidence from mergers and acquisitions. *Journal of Banking and Finance*, 35(7), 1753– 1761. https://doi.org/10.1016/j.jbankfin.2010.12.006
- Attah-Boakye, R., Guney, Y., Hernandez-Perdomo, E., & Mun, J. (2021). Why do some merger and acquisitions deals fail? A global perspective. *International Journal of Finance and Economics*, 26(3), 1–32. https://doi.org/10.1002/ijfe.2039
- Balasubramanian, S., Shukla, V., Mangla, S., & Chanchaichujit, J. (2021). Do firm characteristics affect environmental sustainability? A literature review-based assessment. *Business Strategy and the Environment*, 30(2), 1389–1416. https://doi.org/10.1002/bse.2692
- Barros, V., Guedes, M. J., Santos, P., & Sarmento, J. M. (2021). Does CEO turnover influence dividend policy? *Finance Research Letters*, 1–7. https://doi.org/10.1016/j.frl.2021.102085
- Barros, V., Verga Matos, P., Miranda Sarmento, J., & Rino Vieira, P. (2021). M&A activity as a driver for better ESG performance. *Technological Forecasting and Social Change*, 1–8. https://doi.org/10.1016/J.TECHFORE.2021.121338
- Bena, J., & Li, K. (2014). Corporate Innovations and Mergers and Acquisitions. *Journal of Finance*, 69(5), 1923–1960. https://doi.org/10.1111/jofi.12059
- Benabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica*, 77(305), 1–19. https://doi.org/10.1111/j.1468-0335.2009.00843.x
- Bereskin, F., Byun, S. K., Officer, M. S., & Oh, J. M. (2018). The Effect of Cultural Similarity on Mergers and Acquisitions: Evidence from Corporate Social Responsibility. *Journal of Financial and Quantitative Analysis*, 53(5), 1995–2039. https://doi.org/10.1017/S0022109018000716

Berk, J., & DeMarzo, P. (2017). Corporate Finance, 4th Edition, Global Edition. In Pearson.

- Berman, S. L., Wicks, A. C., Kotha, S., & Jones, T. M. (1999). Does Stakeholder
  Orientation Matter? The Relationship between Stakeholder Management Models and
  Firm Financial Performance. *Source: The Academy of Management Journal*, 42(5), 488–506. https://www.jstor.org/stable/256972
- Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008

- Bose, S., Minnick, K., & Shams, S. (2021). Does carbon risk matter for corporate acquisition decisions? *Journal of Corporate Finance*, 70, 1–21. https://doi.org/10.1016/j.jcorpfin.2021.102058
- Botosan, C. A. (2006). Disclosure and the cost of capital: What do we know? *Accounting and Business Research*, *36*(SPEC. ISS), 31–40. https://doi.org/10.1080/00014788.2006.9730042
- Bouzgarrou, H., & Navatte, P. (2013). Ownership structure and acquirers performance: Family vs. non-family firms. *International Review of Financial Analysis*, 27, 123–134. https://doi.org/10.1016/j.irfa.2013.01.002
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns. *Journal of Financial Economics*, 14(1), 3–31. https://doi.org/10.1016/0304-405x(85)90042-x
- Chang, S. (1998). Takeovers of privately held targets, methods of payment, and bidder returns. *Journal of Finance*, *53*(2), 773–784. https://doi.org/10.1111/0022-1082.315138
- Chatterji, A. K., Levine, D. I., & Toffel, M. W. (2009). How well do social ratings actually measure corporate social responsibility? *Journal of Economics and Management Strategy*, 18(1), 125–169. https://doi.org/10.1111/j.1530-9134.2009.00210.x
- Cheng, B., Ioannou, I., & Serafeim, G. (2014). Corporate social responsibility and access to finance. *Strategic Management Journal*, *35*(1), 1–24. https://doi.org/10.1002/smj.2131
- Cohen, L., Gurun, U. G., & Nguyen, Q. (2021). The ESG Innovation Disconnect: Evidence from Green Patenting. SSRN Electronic Journal, 1–46. https://doi.org/10.2139/ssrn.3718682
- Cox, D. R. (1984). Interaction. International Statistical Review, 52(1), 1–24.
- Damodaran, A. (2011). The Value of Synergy. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.841486
- Delis, M. D., de Greiff, K., & Ongena, S. R. G. (2019). Being Stranded with Fossil Fuel Reserves? Climate Policy Risk and the Pricing of Bank loans. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3451335
- Directive of the European Parliament and of the council. (2021). *European Commission, Bruessel*, 820–856. https://doi.org/10.5040/9781782258674.0035
- Dorfleitner, G., Halbritter, G., & Nguyen, M. (2015). Measuring the level and risk of corporate responsibility - An empirical comparison of different ESG rating approaches. *Journal of Asset Management*, 16(7), 450–466. https://doi.org/10.1057/jam.2015.31

- Duarte, D., & Barros, V. (2018). Corporate tax avoidance and profitability followed by mergers and acquisitions. *Corporate Ownership and Control*, 15(2–1), 148–160. https://doi.org/10.22495/cocv15i2c1p2
- Eliwa, Y., Aboud, A., & Saleh, A. (2021). ESG practices and the cost of debt: Evidence from EU countries. *Critical Perspectives on Accounting*, 79. https://doi.org/10.1016/j.cpa.2019.102097
- Farooq Ahmad, M., de Bodt, E., Bollaert, H., Boubakri, N., Calcagno, R., Charpentier, C., Chen, T., Derrien, F., Facio, M., Frijns, B., Guedhami, O., Harford, J., Lapied, A., Levasseur, M., Lobez, F., Schwienbacher, A., & Su, C.-H. (2015). French Finance Association (AFFI) PhD workshop 2014 (France), Financial Management Association Europe (FMA) 2014 (Netherlands). AFFI. https://ssrn.com/abstract=2409308
- Feng, X. (2021). The role of ESG in acquirers' performance change after M&A deals. Green Finance, 3(3), 287–318. https://doi.org/10.3934/GF.2021015
- Franklin, J. (2019). ESG now a key factor in M&A. *International Financial Law Review*. https://www.proquest.com/docview/2307036528
- Freeman, R. E. E., & McVea, J. (2001). A Stakeholder Approach to Strategic Management. SSRN Electronic Journal, 1–32. https://doi.org/10.2139/ssrn.263511
- Friedman, M. (2007). The Social Responsibility of Business Is to Increase Its Profits. Corporate Ethics and Corporate Governance, 173–178. https://doi.org/https://doi.org/10.1007/978-3-540-70818-6\_14
- Gaughan, P. A. (2017). Mergers, Acquisitions, and Corporate Restructurings (7th ed.). John Wiley & Sons Inc. https://doi.org/https://doi.org/10.1002/9781119380771
- Gault, F. (2018). Defining and measuring innovation in all sectors of the economy. *Research Policy*, 47(3), 617–622. https://doi.org/10.1016/j.respol.2018.01.007
- Giese, G., Lee, L.-E., Melas, D., Nagy, Z., & Nishikawa, L. (2015). Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance. *The Journal of Portfolio Management*, 45(5), 69–83. https://doi.org/https://doi.org/10.3905/jpm.2019.45.5.069
- Golubov, A., Yawson, A., & Zhang, H. J. (2015). Extraordinary Acquirers. Journal of Financial Economics (JFE), 1–30. https://doi.org/http://dx.doi.org/10.2139/ssrn.2326420
- Greenhalgh, C., & Rogers, M. (2010). Innovation, Intellectual Property, and Economic Growth. In *Journal of Financial Economics (JFE)*. Princeton University Press. https://doi.org/10.2307/j.ctt1zgwjjb

- Gregory, A. (2003). An examination of the long run performance of UK acquiring firms. *Journal of Business Finance and Accounting*, 24(7–8). https://doi.org/10.1111/1468-5957.00146
- Griffin, P. A., Lont, D. H., Sun, Y., thank Shannon Anderson, W., Bradbury, M., Cahan, S., Chaput, S., Clarkson, P., Dorata, N., Edelen, R., Hay, D., Monroe, G., & Richardson, G. (2012). *The Relevance to Investors of Greenhouse Gas Emission Disclosures*. 1–41. https://doi.org/http://dx.doi.org/10.2139/ssrn.1735555
- Hart, O., & Zingales, L. (2017). Companies should maximize shareholder welfare not market value. *Journal of Law, Finance, and Accounting*, 2(2), 243–275. https://doi.org/10.1561/108.00000022
- Hillman, A. J., & Keim, G. D. (2001). Shareholder Value, Stakeholder Management, and Social Issues: What's the Bottom Line? *Management Journal*, 22(2), 125–139. https://www.jstor.org/stable/3094310
- Houston, J. F., & Shan, H. (2019). Corporate ESG Profiles and Banking Relationships. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3331617
- Ioannou, I., & Serafeim, G. (2012). What drives corporate social performance the role of nation-level institutions. *Journal of International Business Studies*, 43(9), 834–864. https://doi.org/10.1057/jibs.2012.26
- Kengelbach, J., Berberich, U., & Keienburg, G. (2015). *Why Deals Fail*. https://www.bcg.com/publications/2015/why-deals-fail
- Kerber Ross. (2021, September 10). Harvard University to end investment in fossil fuels | Reuters. https://www.reuters.com/world/us/harvard-university-will-allow-fossil-fuelinvestments-expire-2021-09-10/
- Khan, M., Serafeim, G., & Yoon, A. (2016). Corporate Sustainability: First Evidence on Materiality. *The Accounting Review*, 91(6), 1697-1724. https://doi.org/http://dx.doi.org/10.2139/ssrn.2575912
- Kim, J. Y., Haleblian, J., & Finkelstein, S. (2011). When firms are desperate to grow via acquisition: The effect of growth patterns and acquisition experience on acquisition premiums. *Administrative Science Quarterly*, 56(1). https://doi.org/10.2189/asqu.2011.56.1.026
- Kim, Y., Park, M. S., & Wier, B. (2012). Is earnings quality associated with corporate social responsibility? *Accounting Review*, 87(3), 761–796. https://doi.org/10.2308/accr-10209

- Kothari, S. P., & Warner, J. B. (2007). Econometrics of Event Studies. Handbook of Empirical Corporate Finance SET, 1, 3–36. https://doi.org/10.1016/B978-0-444-53265-7.50015-9
- Krishnakumar, D., & Sethi, M. (2016). Post IPO Mergers and Acquisitions Strategies: Evidence from India. *Indian Journal of Science and Technology*, 9(15), 1–8. https://doi.org/10.17485/ijst/2016/v9i15/92096
- Krishnamurti, C., Shams, S., Pensiero, D., & Velayutham, E. (2019). Socially responsible firms and mergers and acquisitions performance: Australian evidence. *Pacific Basin Finance Journal*, 57. https://doi.org/10.1016/j.pacfin.2019.101193
- Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics*, 115(2), 304–329. https://doi.org/10.1016/j.jfineco.2014.09.008
- Kwon, O., Lim, S., & Lee, D. H. (2018). Acquiring startups in the energy sector: a study of firm value and environmental policy. *Business Strategy and the Environment*, 27(8), 1376–1385. https://doi.org/10.1002/bse.2187
- Lewis, A., & McKone, D. (2016). So Many M&A Deals Fail Because Companies Overlook This Simple Strategy. *Harvard Business Review Digital Articles*.
- Liang, H., & Renneboog, L. (2017). On the Foundations of Corporate Social Responsibility. *Journal of Finance*, 72(2), 853–910. https://doi.org/10.1111/jofi.12487
- Lodh, A. (2020, February 25). *ESG and the cost of capital MSCI*. MSCI. https://www.msci.com/www/blog-posts/esg-and-the-cost-of-capital/01726513589
- Loughran, T., & Ritter, J. R. (2000). Uniformly least powerful tests of market efficiency. Journal of Financial Economics, 55(3), 361–389. https://doi.org/10.1016/S0304-405X(99)00054-9
- Mackenzie Michael, & Nauman Billy. (2021, January 26). BlackRock pushes companies to adopt 2050 net zero emissions goal | Financial Times. https://www.ft.com/content/a71feaac-d3f4-4e76-a60c-c68924b06dfd
- Mackinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1), 13–39.
- Malik, M. (2014). The impact of targets' social performance on acquisition premiums. In *ProQuest Dissertations and Theses*.
- Masulis, R. W., Wang, C., & Xie, F. (2007). Corporate governance and acquirer returns. *Journal of Finance*, 62(4), 1851–1889. https://doi.org/10.1111/j.1540-6261.2007.01259.x

- Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *Accounting Review*, 89(2), 695–724. https://doi.org/10.2308/accr-50629
- Mitchell, M. L., & Stafford, E. (2000). Managerial decisions and long-term stock price performance. *Journal of Business*, 73(3), 287–329. https://doi.org/10.1086/209645
- Moeller, S. B., & Schlingemann, F. P. (2005). Global diversification and bidder gains: A comparison between cross-border and domestic acquisitions. *Journal of Banking and Finance*, 29(3), 533–564. https://doi.org/10.1016/S0378-4266(04)00047-0
- Ng, A. C., & Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance*, 34, 128–149. https://doi.org/10.1016/j.jcorpfin.2015.08.003
- OECD. (2021, October 27). G20 economies are pricing more carbon emissions but stronger globally more coherent policy action is needed to meet climate goals, says OECD.
   https://www.oecd.org/tax/g20-economies-are-pricing-more-carbon-emissions-but-stronger-globally-more-coherent-policy-action-is-needed-to-meet-climate-goals-says-oecd.htm
- Petrova, M., Shafer, M. T., & Whitman, M. J. (2010). Post-Acquisition Performance: A Propensity Score Matching Approach.

```
http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.606.4230
```

- Proposal for a Directive of the European Parliament and of the Council. (2020). In *Fundamental Texts On European Private Law*. https://doi.org/10.5040/9781782258674.0035
- Refinitiv. (2021). Environmental, Social and Governance (ESG) scores from Refinitiv. https://www.refinitiv.com/content/dam/marketing/en\_us/documents/methodology/refini tiv-esg-scores-methodology.pdf
- SASB. (2021). *Materiality Finder Overview SASB*. https://www.sasb.org/standards/materiality-finder/
- Seltzer, L., Starks, L. T., & Zhu, Q. (2020). Climate Regulatory Risks and Corporate Bonds. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3563271
- Shapira, R., & Zingales, L. (2018). Is Pollution Value-Maximizing? The DuPont Case. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3037091
- Sharma, P., Panday, P., & Dangwal, R. C. (2020). Determinants of environmental, social and corporate governance (ESG) disclosure: a study of Indian companies. *International*

*Journal of Disclosure and Governance*, *17*(4), 208–2017. https://doi.org/10.1057/s41310-020-00085-y

- 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. https://doi.org/10.1002/bse.2475
- Tohidi, H., & Jabbari, M. M. (2012). The important of Innovation and its Crucial Role in Growth, Survival and Success of Organizations. *Procedia Technology*, 1, 535–538. https://doi.org/10.1016/j.protcy.2012.02.116
- Trichterborn, A., Zu Knyphausen-Aufseß, D., & Schweizer, L. (2016). How to improve acquisition performance: The role of a dedicated M&A function, M&A learning process, and M&A capability. *Strategic Management Journal*, 37(4). https://doi.org/10.1002/smj.2364
- United Nations. (2015). Adoption of the Paris Agreement. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement
- Utz, S. (2019). Corporate scandals and the reliability of ESG assessments: evidence from an international sample. *Review of Managerial Science*, *13*(2), 483–511. https://doi.org/10.1007/s11846-017-0256-x

Wooldridge, J. M. (2012). *Introductory econometrics: A modern approach* (5th ed.). Thomson South-Western.

# 11. Appendix

Variable Name	Definition	Source
Deal-specific variables:		
Cross border Relative size Serial acquiror Cash/share payment	1 if deal is International Deal value / acquiror market capitalization More than 5 deals in the last 3 years 1 if cash financed, 0 if share payment	SDC SDC SDC / Refinitiv SDC
Industry relates	1 if transaction is in the same industry	SDC
Financial variables		
Price-to-book Profitability	Market capitalization to book value of equity - 4 week prior (common equity) Earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by	SDC Refinitiv
	book value of total assets Net Sales 2-Year Growth Rate: Growth, in percentage terms, of net sales over the	Refinitiv
Sales growth Cash	preceding two year period Logarithm of cash and short-term investments divided by the book value of total asset	Refinitiv
Leverage	Book value of debt (sum of current debt and long-term debt) divided by book value of total asset	Refinitiv
Capex / total assets	Capital expenditure / Total assets	Refinitiv
R&D to assets	Research and development (R&D) expenditure divided by the book value of total assets.	Refinitiv Refinitiv
Size R&D expenditure Emission score	Logarithm of total assets R&D divided on total assets Emission score retrieved from Refinitiv	Refinitiv Refinitiv
ΔES Materiality	The change in emission score from one year to the next The industry materiality of GHG emissions	Refinitiv SASB
ESG variables		
Refinitiv ESG emissions reduction score	The emission reduction score measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes	Refinitiv
Refinitiv ESG innovation score	The innovation score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed products.	Refinitiv
Refinitiv ESG resource use score	The resource use score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management.	Refinitiv
SASB - Sustainability issues		
SASB GHG emission issue	"The category addresses direct (Scope 1) greenhouse gas (GHG) emissions that a company generates through its operations. This includes GHG emissions from stationary (e.g., factories, power plants) and mobile sources (e.g., trucks, delivery vehicles, planes), whether a result of combustion of fuel or non-combusted direct releases during activities such as natural resource extraction, power generation, land use, or biogenic processes. The category further includes management of regulatory risks, environmental compliance, and reputational risks and opportunities, as they related to direct GHG emissions. The seven GHGs covered under the Kyoto Protocol are included within the category—carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3)."	SASB
Fixed effects		
Industry fixed effects Time fixed effects Country Fixed Effect Firm-specific Fixed Effect	SASB industry classification dummy Time variable dummy Country dummy Company dummy	SDC SDC SDC SDC

### Table 15 - Definition and explanations of terms and variables

Industry	Score	Industry	Score
Apparel, Accessories Footwear	0	Home Builders	0
Appliance Manufacturing	0	Real Estate	0
Building Products & Furnishings	0	Real Estate Services	0
E-Commerce	0	Waste Management	1
Household & Personal Products	0	Water Utilities & Services	0
Multiline and Specialty Retailers & Distributors	0	Biofuels	0
Toys & Sporting Goods	0	Forestry Management	0
Coal Operations	1	Fuel Cells & Industrial Batteries	0
Construction Materials	1	Pulp & Paper Products	1
Iron & Steel Producers	1	Solar Technology & Project Developers	0
Metals & Mining	1	Wind Technology & Project Developers	0
Oil & Gas – Exploration & Production	1	Aerospace & Defense	0
Oil & Gas – Midstream	1	Chemicals	1
Oil & Gas – Refining & Marketing	1	Containers & Packaging	1
Oil & Gas – Services	1	Electrical & Electronic Equipment	0
Asset Management & Custody Activities	0	Industrial Machinery & Goods	0
Commercial Banks	0	Advertising & Marketing	0
Consumer Finance	0	Casinos & Gaming	0
Insurance	0	Education	0
Investment Banking & Brokerage	0	Hotels & Lodging	0
Mortgage Finance	0	Leisure Facilities	0
Security & Commodity Exchanges	0	Media & Entertainment	0
Agricultural Products	1	Professional & Commercial Services	0
Alcoholic Beverages	0	EMS & ODM	0
Food Retailers & Distributors	1	Hardware	0
Meat, Poultry & Dairy	1	Internet Media & Services	0
Non-Alcoholic Beverages	1	Semiconductors	1
Processed Foods	0	Software & IT Services	0
Restaurants	0	Telecommunication Services	0
Tobacco	0	Air Freight & Logistics	1
Biotechnology & Pharmaceuticals	0	Airlines	1
Drug Retailers	0	Auto Parts	0
Health Care Delivery	0	Automobiles	0
Health Care Distributors	1	Car Rental & Leasing	0
Managed Care	0	Cruise Lines	1
Medical Equipment & Supplies	0	Marine Transportation	1
Electric Utilities & Power Generators	1	Rail Transportation	1
Engineering & Construction Services	0	Road Transportation	1
Gas Utilities & Distributors	0	·	

### Table 16 - Overview of industries used by SASB and coherent materiality score

Country	Fama-French factors used
China	Asia Pacific
Taiwan	Asia Pacific
United States	US
Australia	Asia Pacific
Brazil	Emerging markets
Netherlands	Europe
Japan	Japan
Switzerland	Europe
Ireland	Europe
United Kingdom	Europe
Bermuda	US
Hong Kong	Asia Pacific
Canada	North America
France	Europe
Luxembourg	Europe
South Africa	Emerging markets
Germany	Europe
Austria	Europe
Italy	Europe
Israel	Emerging markets
Sweden	Europe
Finland	Europe
Norway	Europe
Belgium	Europe
Singapore	Asia Pacific
South Korea	Asia Pacific
Spain	Europe
India	Emerging markets
Poland	Europe
Gibraltar	Europe
Greece	Europe
United Arab Emirates	Emerging markets
Denmark	Europe
Thailand	Asia Pacific
Mexico	Emerging markets

 Table 17 - Overview of the country or regional Fama-French factors used

#### Table 18 - SASB definition of materiality

Issue is likely to be material for more than 50% of industries in the sector
 Issue is likely to be material for fewer than 50% of industries in the sector

 $\hfill \Box$  Issue is not likely to be material for any of the industries in the sector

arity

Factor	1	2	3	4
$\frac{TARGET}{ACQ}ES$			1.021	1.042
M&A	1.304	1.279		
Relative Deal Size	1.210	1.227	1.031	1.058
Ln (Size)	1.157	1.154	1.083	1.083
Leverage	1.065	1.066	1.185	1.188
P/B	1.007	1.007	1.097	1.098
R&D/Assets	1.110	1.110	1.169	1.169
Capex/Assets	1.088	1.091	1.138	1.138
Factor (Year)	1.015	1.015	1.010	1.011
Factor (Country)	1.014	1.014	1.029	1.030

VIF test for OLS in hypothesis 1

#### VIF test for OLS in hypothesis 2

Factor	1	2	3
ΔES0 x Materiality (T-1 to T)	1.300		
$\Delta$ ES1 x Materiality (T to T+1)		1.269	
$\frac{TARGET}{ACQ}ES \ x \ Materilaity$			1.694
ΔES0 (T-1 to T)	1.326		
ΔES1 (T to T+1)		1.278	
$\frac{TARGET}{ACQ}ES$			1.762
Materiality	1.204	1.215	1.762
Ln (Size)	1.968	1.963	1.178
Leverage	1.121	1.122	2.009
P/B	1.101	1.101	1.224
R&D/Assets	1.227	1.226	1.146
Profitability	1.159	1.161	1.293
ACQ 2 Year Growth	1.034	1.034	1.148
ACQ Emission score, T-1	1.319	1.277	
Ln (Cash)	1.911	1.909	1.885
Industry Related	1.084	1.084	1.112
Relative Deal Size	1.104	1.105	1.365
Factor (Payment_method)	1.096	1.095	1.102
Factor (Country)	1.025	1.024	
Factor (Year)	1.036	1.037	1.051

Note: Values greater than 10 indicates multicollinearity

Table 20 - Breusch-Pagan	Test for Heteroskedasticity
--------------------------	-----------------------------

OLS - Hypothesis 1				
Model	(1)	(2)	(3)	(4)
Statistic	35.421	36.302	11.201	10.945
Parameter	7	7	7	7
P-value	9.32e-6	6.359e-6	0.130	0.141

#### OLS - Hypothesis 2, short-term returns

Model	(1)	(2)	(3)
Statistic	104.110	104.290	15.073
Parameter	13	13	12
P-value	2.635e-16	2.434e-16	0.238

### OLS - Hypothesis 2, long-term returns

OLS - Hypothesis 2, long-term returns			
Model	(1)	(2)	(3)
Statistic	31.738	33.515	12.252
Parameter	13	13	12
P-value	0.003	0.001	0.426

**Note:** A P-value of < 5% indicates heteroskedasticity

	De	ependant Vario	able
		AR	
	(1)	(2)	(3)
( $\Delta$ ES T-1 to T) x Treatment	0.008		
x Industry Materiality x Post M&A	(0.017)		
		0.000	
(Δ ES T to T+1) x Treatment x Industry Materiality x Post M&A		0.002 (0.019)	
x muustry Materianty x Post M&A		(0.019)	
$\frac{ARGET}{ACO}$ ES x Industry Materiality x Post M&A			-0.214 (0.733)
πεφ			(0.755)
( $\Delta$ ES T-1 to T) x Industry Materiality x Post M&A	-0.009		
	(0.013)		
		-0.005	
( $\Delta$ ES T to T+1) x Industry Materiality x Post M&A		(0.011)	
			0 - 1 -
<u>ARGET</u> ACQ ES x Post M&A			0.713
Αυξ			(0.495)
(Δ ES T-1 to T) x Treatment x Post M&A	0.008		
	(0.012)		
		0.011	
(Δ ES T to T+1) x Treatment x Post M&A		-0.011 (0.013)	
		(0.013)	
(Δ ES T-1 to T) x Post M&A	0.013		
	(0.012)		
(Δ ES T to T+1) x Post M&A		0.007	
, , , , , , , , , , , , , , , , , , ,		(0.010)	
	0.078	0.097	0.085
Industry Materiality x Treatment x Post M&A	(0.274)	(0.276)	(0.504)
	0.015	-0.027	0.158
Treatment x Post M&A	(0.156)	(0.152)	(0.294)
	0.071	0.076	0.052
Industry Materiality x Post M&A	(0.181)	(0.180)	(0.232)
	(0.101)	(0.100)	(0.252)
Post M&A	0.364	0.396	0.286
	(0.446)	(0.451)	(0.666)
Observations	5,159	5,159	3,019
Firm-Specific Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes p<0.1; **p<0.0	Yes

### Table 21 - Quadruple difference-in-difference with all interaction terms