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Behind the green curtain

Unveiling the short and long-term intricate financial implications of carbon disclosure and carbon performance

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Abstract

The urgency of addressing climate change has directed corporate focus towards sustainable operations, particularly in carbon management. This paper examines the dynamic interplay between carbon disclosure, carbon performance and financial performance among the world's largest publicly listed companies applying a random-effect multiple linear and polynomial regression model, utilizing an extensive dataset of 12,687 firm-year observations from 2014 to 2023. The findings present a positive influence of carbon disclosure on financial performance in both the short and long-term, highlighting the strategic value of transparency. Notably, the paper underscores the long-term financial benefits of sustained disclosure efforts for companies with initially low levels of carbon disclosure, while companies with high initial levels should maintain the elevated disclosure standards in both the short and long-term. Further analyses differentiates strategies for carbon-intensive and non-intensive industries, of which the former should leverage early financial gains from disclosure, while the latter should focus on sustained strategies for long-term financial benefits as stakeholder appreciation grows. Interestingly, the study reveals that carbon performance is best described by an inverse U-shaped relationship in both the short and long-term. The relationship exhibits diminishing marginal returns beyond a certain carbon performance threshold, especially in the short-term. Overall, the analyses suggests that the market reacts more favourable to disclosure about carbon emissions than to actual reduction of emissions. This could incentivize firms to concentrate on disclosure rather than substantive actions, potentially opening doors for carbon greenwashing. This study contributes to the growing body of literature on corporate sustainability by providing empirical evidence on the financial implications of carbon management practices. This comprehensive analysis offers new perspectives and policy implications, encouraging more informed decision-making in the evolving landscape of corporate sustainability. Aiming for a future where sustainable practices are not just ethical imperatives but crucial drivers of economic prosperity.

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1. Introduction

The urgency of our times calls for an internationally shared purpose of carbon reduction, a cornerstone in achieving the ambitious goals set by the Paris Agreement to curtail temperature rise to below 2°C, and since the activation of the Kyoto protocol. Governments worldwide have embraced green strategies as fundamental, recognizing that "going green" safeguards the planet and yields sustainable returns. Potential decarbonization of operations and products could potentially result in 9 trillion to 12 trillion annual sales by 2023, due to a demand shift of customer and capital to a low-carbon economy (McKinsey, 2023). Companies are navigating a complex operational landscape marked by diverse initiatives and regulatory frameworks, prompting calls for comprehensive climate policies at the national and regional levels (Howard-Grenville et al., 2014). The International Financial Reporting Standards (IFRS) has released two global sustainability disclosure standards in June 2023 and is active since January 2024. The first standard focuses on disclosing sustainability-related risk and opportunities, while the second mandates the disclosure of material climate-related information (The Economist Intelligence, 2023). Reporting and transparency regarding a companies' carbon footprint, also called carbon disclosure, and their vulnerability to climate-related risk, exposes important investment information, enhances investment decisions and regulations (European Central Bank, 2023). Besides an increased carbon disclosure, companies also engage in carbon performance activities, which lead to realized carbon reduction, cost saving through energy efficiency and waste management, competitive advantages, and long-term sustainability. As a result, companies, besides a moral obligation, also recognize that it can be profitable and value-enhancing to report and reduce carbon emissions.

Where carbon performance focuses on concrete actions taken by a company to reduce its carbon emissions, carbon disclosure focuses on the transparency and reporting regarding its environmental efforts. Companies often launch carbon reduction programs with the intention of receiving financial benefits, while these efforts don't align with their core strategies, because of a lack of understanding about the trade-off between carbon performance, carbon disclosure, and financial performance (Eccles & Serafeim, 2013). Hence, additional data, research and collaborative knowledge-sharing is required to encourage entities to a adopt a less Greenhouse Gas (GHG) emission way of operating. Additionally, "the gap between corporate decarbonization claims and tangible action has widened" (In & Schumacher, 2021). This paper answers therefore the question:

What is the impact of carbon disclosure and carbon performance on financial performance of the world's largest companies in the short and long-term?

In recent years, the focus has shifted to GHG emissions, and the number of papers about the effect of carbon risk and carbon disclosure on financial performance increased significantly, due to a combination of more regulation, pressure from stakeholders and better data availability (Wang, 2023). The number of published papers about carbon disclosure for example has grown incrementally up to 2013, followed by years of exponential growth until this date (Mishra et al., 2023). This emphasizes the high relevance of this paper.

The relationship between carbon disclosure, carbon performance, and financial performance has been studied extensively with varying outcomes. The previous studies predominantly demonstrate a positive relationship between carbon disclosure and financial performance, with a notable contribution from Clarkson et al. (2008), who provide a categorization of environmental accounting literature. Alsaifi et al. (2020) highlight the beneficial relationship between carbon disclosure and financial performance, indicating that consistent participation in voluntary carbon disclosure leads to higher financial performance and a long-term competitive advantage. Similarly, Matsumura et al. (2014) and He et al. (2013) discuss the positive implications of reducing information asymmetry through carbon disclosure. In contrast, studies by Griffin et al. (2017), Sullivan & Gouldson (2012), and Lu et al. (2021) offer a more nuanced view, addressing the intrinsic and sometimes negative effect of carbon disclosure in certain contexts.

The interplay between carbon performance and financial performance is intricate as well, as discussed by Busch and Hoffmann (2011) who explore both competitive advantage and stakeholder theories. Studies by Nishitani and Kobubu (2012), Trinks et al. (2020), and Misani & Pogutz (2015) generally find a positive impact of carbon performance on financial performance, highlighting the benefits of environmental strategies and carbon efficiency. Conversely, research by Rokhmawati et al. (2015), Rokhmawati et al. (2017), and Lewandowski (2017) present the challenges and potential negative impact of carbon performance, thereby stressing the complex and diverse relationship.

This study is a complementary to the existing literature in several ways. As seen in the different results, the research is rather intricate and heterogeneous and many research papers do not strictly distinguish between carbon disclosure and carbon performance (Velte et al., 2020). At first, it extends the existing literature on a fundamental economic and environmental topic in times of a climate crisis by examining the effect of carbon disclosure and carbon performance on financial performance. Secondly, the effect of carbon disclosure and carbon performance on financial performance has not, separately, been studied substantially in the same research. As a result, this paper is able to study the difference between substantive carbon actions and potentially misleading carbon greenwashing. Thirdly, has the combination of market-based variables and accounting-based variables not been studied intensively. The coherence between the variables will reveal a difference between short-term and long-term effects and investor reactions to carbon exposing actions. Lastly, recent studies have mostly focused on one country or industry, where this paper focuses on a large dataset consisting of multiple industries and countries.

For this study, the world's largest listed firms, given their global public exposure, are selected based on their market value. The final sample consists of 12,687 firm-year observations after exclusion of missing values and specific industries. Carbon data is retrieved from the ESG Database from Refinitiv Eikon from 2014 up to 2023. Eikon owns one of the most extensive ESG datasets, covering over 80% of the global market capitalization (Refinitiv Eikon, 2023a). The financial data is retrieved from the Eikon database as well, to make sure that the data collection of the variables is aligned.

Based on the study mentioned earlier on the relationship between carbon disclosure and financial performance, a positive relationship is expected in both the short and long-term. It results in an increased shareholder satisfaction in the short-term, due to more transparency, and an enhanced competitive advantage in the long-term. The relationship between carbon performance and financial performance is expected to be positive in the short-term by picking low-hanging fruits of carbon performance improvements or U-shaped by following Friedman's trade-off theory. It is expected to be positive in the long-term as well, by establishing and utilizing new capabilities which lead to long-term carbon performance and financial performance enhancements or a potential diminishing relationship due to carbon improvements saturation.

The structure of this paper continues with Chapter 2, which presents the theoretical framework which is used as foundation for this paper. Further, hypotheses are formulated in Chapter 3 based on theory and the effect found in prior research. Methodology is outlined in Chapter 4, describing the sample selection, variables, and models used, leading up to the results discussed in Chapter 5. Chapter 6 discusses the robustness of the study, Chapter 7 ends with a conclusion, and Chapter 8 presents a list of references.

2. Theoretical framework

This theoretical framework serves as the intellectual foundation upon which the empirical research is constructed, incorporating the most important definitions, theories and perspectives about carbon disclosure, carbon performance and financial performance.

2.1 Carbon disclosure

Carbon disclosure is the informational and organizational infrastructure for the reporting of GHG emissions quantification, evaluation, and management, and their associated risks and opportunities (Kolk et al., 2008). In the 1990s, companies shifted from developing strategies opposing climate change regulations to responses that support the reduction of GHG emissions. Companies facing regulatory risk had the option to innovate through improvements of internal processes or to compensate emissions by participating on the emission trading market (Kolk & Pinkse, 2005). Carbon trading refers to trading GHG emissions in a market-based system to combat climate change. Various emission trading schemes exist worldwide, differing in size, scope, and design (voluntary or unvoluntary) but all share the goal of reducing emissions where its most cost-effective (Perdan & Azapagic, 2011). For example, the largest mandatory operational "cap-and-trade" trading scheme, the EU ETS, which requires emission accounting and trading of companies in some European regions. In the beginning of 2000's, firms in the transport and energy sector started to invest significantly in low carbon-intensive technologies and participated in different voluntary trading schemes. Causing carbon trading to be the underlying accelerator of a global climate regime by creating a corporate governance approach that is decentralized, market-driven and fragmented (Kolk et al., 2008; Aulisi et al., 2005). All new GHG emission-reducing innovations require an increased level of carbon disclosure, as a result, indirectly raising the pressure to measure and report carbon emissions.

Carbon disclosure can be divided into two categories, mandatory carbon disclosure and voluntary carbon disclosure. Some arguments advocate mandatory over voluntary carbon disclosure. Firstly, overall carbon disclosure lacks both quality and availability which resulted in some countries to increase mandatory carbon disclosure, which enhances availability. Moreover, since mandatory carbon disclosure imposes standardized reporting requirements for companies, it results in more uniform and, therefore, better comparable collected data (Jouvenot & Krueger, 2019). Secondly, from a legal perspective, it supports companies in identifying potential cost saving and help to address the risk and opportunities related to climate (Raingold, 2010). Thirdly, mandatory carbon disclosure leads to less information asymmetry, considering a minimum emission information benchmark that needs to be made public. In contrast with voluntary disclosure, where firms can decide for themselves to disclosure or withhold. Leading to a potential adverse selection problem where managers only disclose when they have positive information to declare (Schiemann & Sakhel, 2019).

The momentum surrounding voluntary carbon disclosure has been significantly increasing over the last recent years due to a variety of different voluntary initiatives and frameworks, such as the Carbon Disclosure Project (CDP), the Task Force on Climate-related Financial Disclosures (TCFD, Science-based Target Initiative (SBTi), Carbon Credit Xchange or the Verified Carbon Standard (VCR). Therefore, on the contrary, some arguments and theories support the idea of voluntary carbon disclosure. Firstly, to exploit first-mover advantages, as voluntary carbon disclosure can be used to enhance a company's reputation as an environmental frontrunner and to anticipate mandatory controls (Kolk et al., 2008). Secondly, under mandatory regulation, a company is forced to increase additional costs due to regulation, such as investments in green R&D, which could lead to inefficiency or over-investments (Aghamolla & An, 2021). Thirdly, voluntary carbon disclosure serves a governance function in the context of corporate social responsibility. The broad support of voluntary carbon disclosure plays a crucial role within governance systems. It not only creates a means for being accountable to stakeholders but empowers them to request specific performance standards through carbon disclosure (Brown et al., 2009). The rationale behind voluntary carbon disclosure is substantiated by the stakeholder theory (Clarkson, 1995; Roberts, 1992; van der Laan et al., 2005) and legitimacy theory (Dowling & Pfeffer, 1975). The stakeholder theory explains that managers provide information because it would satisfy the stakeholders' demand for carbon disclosure and transparency. According to the legitimacy theory, firms seek to maintain a favorable image and present themselves in a way that aligns with societal expectations, to appear legit (Freedman & Jaggi, 2011).

Carbon disclosure has a crucial role in shaping organizational transparency and accountability, however, is vulnerable for carbon greenwashing or "carbonwashing". Greenwashing is the "intersection of two firm behaviours: poor environmental performance and positive communication about environmental performance" (Delmas & Burbano, 2011). Voluntary carbon disclosure, where companies willingly disclose carbon emissions, reflect a commitment to environmental responsible behaviour. However, this well-intentioned practice is suspectable to greenwashing since firms may exploit carbon disclosure to project a falsely positive environmental image. Legitimacy theory explains carbon greenwashing, as firms might engage in insincere carbon disclosure to project an image of environmental responsibility without genuinely committing to sustainable practices or by withholding negative information. In contrast, mandatory disclosure, induced by government regulation, strongly decreases the risk of greenwashing yet lacks the genuine commitment evident in voluntary carbon disclosure. As expected, is the likelihood reduced of a company that engages in greenwashing behaviour, while disclosing voluntarily, in countries with more robust climate change regulations (Mateo-Márquez et al., 2022). However, existing carbon reporting standards and associated regulations lack the necessary inclusivity to effectively drive companies toward more engagement in the transitions to low-carbon transition and net-zero climate-related economic goals (In & Schumacher, 2021).

This paper will focus on voluntary carbon disclosure, since it serves an important role in organizational transparency and accountability. It provides a more intriguing empirical depth, due to more informational asymmetry and the research of greenwashing and behavioural finance. Understanding the dynamics can provide valuable insights into the effectiveness and motivations behind voluntary carbon disclosure.

2.2 Carbon performance

This study will focus on structuring hypotheses for an empirical analysis using corporate carbon performance as an independent variable. Carbon performance is described as the quantification of emissions of climate-changing GHG, as well as the measurement of a company's effectiveness of reducing carbon emissions (Hoffmann & Busch, 2008). Firms have been implementing various measures to reduce their GHG emissions, including investments in energy efficiency, low-carbon energy technologies, waste management and by participating in carbon offset markets (Baeumler et al., 2012). The importance of carbon management is underlined by increasing climate change risks and pressure from stakeholders. Consequently, companies are continually striving to enhance their carbon performance.

Prior to detailing environmental performance metrics, an explanation is provided regarding the systematic categorization of GHG emissions into two dimensions. On the one hand, a company utilizes carbon-based resources, such as materials with high carbon-intensity or fossil fuel generated energy. On the other hand, it produces GHG emissions through production processes. Therefore, the total absolute carbon emission, due to a company's presence, do not solely depend on his internal processes, moreover on the industry in which it operates and its role within the supply chain. Hence, the Greenhouse Gas Protocol established GHG accounting and reporting standards to enhance the effectiveness and innovation in GHG management. These standards set operational boundaries by separating direct and indirect absolute emissions (Bhatia et al., 2004). To distinguish between sources of direct and indirect emissions, three scopes are defined for GHG reporting and accounting purposes. Scope 1 are the direct GHG emissions that result from sources that a company possesses or has control over. Indirect GHG emissions result from the company's activities but take place at sources possessed or controlled by other companies. Scope 2 are indirect emissions that result from energy purchases and consumption. Scope 3 emissions aggregate all other indirect emissions, for example emissions produced by companies within the up- and downstream of the value chain. These scopes provide more profound understanding of a company's absolute carbon emissions.

To conduct a more meaningful comparison between companies, relative emissions, unlike absolute emissions, can be of more informative power. Absolute emissions indicate the degree to which a company individually contributes to climate change and relative emissions link emission data to a business metric (Busch & Lewandowski, 2018). Hoffmann and Busch (2008) defined four carbon performance indicators. These indicators are quantitative metrics and measurements used to assess and evaluate a companies' carbon performance. Firstly, carbon intensity characterized by physical aspect, this is a static view approach and quantifies a company's carbon utilization in relationship with a business metric. Secondly, carbon dependency shows variation in the output of carbon performance, a dynamic view based on a companies' dependency on carbon over a specific period. Thirdly, carbon exposure is linked to a company's financial performance in terms of carbon emissions, a static view which reveals the financial consequences of business operations due to carbon usage within a specific year. Lastly, carbon risk assesses the financial impact change of carbon usage within a given period, a dynamic view based on financial dependency over time.

2.3 Financial performance

The financial performance of a firm is defined as the financial outcome resulting from the relationship between organizational characteristics, activities, and surroundings (Combs et al., 2005; Rokhmawati et al., 2017). Hamann et al. (2013) advances Combs' line of thought and categorizes financial performance into four dimensions, which fall under two measurements. Profitability and liquidity are referred to as accounting-based measurements, whereas firm growth and stock market performance are referred to as market-based measurements. Accounting-based method of financial performance measurement refers to the historical performance of organizations based on accounting data presented in annual reports. A firm's liquidity refers to a firm's capacity to meet its current financial liabilities with cash (cash flow from current operations) or near-cash assets ("current" assets that can be converted into cash) (Saleem & Rehman, 2011). Furthermore, firm profitability is described as a firm's ability to effectively utilize production resources to generate financial gains and income and is affected by factors such as a company's financial structure, market share, size, innovational effort, and strategy (Joh, 2003). Market-based measurements reflect the investors' views on the future performance of organizations and are represented by indicators such as the stock price, the market cap, dividends, and stock volatility. Hence, accounting-based measurements reflect historical performance, indicating a short-term focus, and market-based measurements entail a forward-looking perspective, therefore, in contrary, can be seen as long-term perspective (Hamann et al., 2013).

3. Hypotheses development

Clarkson et al. (2008) categorized the existing environmental accounting literature into three groups. The first focuses on valuation relevance when examining the effect of corporate disclosure of environmental performance information. The second research examines determinants of discretionary disclosure of environmental liabilities. The third group studies the relationship between environmental disclosure and environmental performance. This study contributes to the line of thought of the latest group, concentrating specifically on distinguishing between environmental disclosure and performance, focusing even more specifically on relevant carbon emissions.

This chapter consists of multiple sections, all of which will follow the order explained hereafter. These sections jointly form the foundation of this research about the intricate effect of carbon disclosure and carbon performance on financial performance. Firstly, it will present relevant theories that elaborate and support the observed effect. Secondly, this section aims to present a comprehensive overview of the existing research on that effect. Lastly, it will utilize the presented theoretical framework and literature review to develop the hypotheses. Four hypotheses have been formulated to answer the research question: *What is the impact of carbon disclosure and carbon performance on financial performance of the world's largest companies in the short and long-term?*

3.1 Carbon disclosure and financial performance

3.1.1 Underlying dynamics and principles

Carbon disclosure influences a firm's financial performance in various ways. The previously mentioned aspects of financial performance, and carbon disclosure theory, such as the resource-based view, information asymmetry, and signaling theory, play a crucial role in explaining this relationship.

Carbon disclosure influences financial performance partly through a competitive environmental strategy. In line with the resource-based view (RBV) theory, which considers a firms' tangible and intangible resources that are valuable, difficult to imitate and non-substitutable as essential capabilities to establish a competitive advantage (Barney, 2001). Therefore, carbon disclosure can be seen as a strategic resource by increasing transparency and accountability regarding a firm's environmental impact. Hereby providing value both in terms of customer trust and stakeholder confidence. Furthermore, complimentary to the RBV theory, it can enhance a firm's competitive advantage, explained by a decrease of information asymmetry, and as differentiator from poor performing competitors (Alsaifi et al., 2020). This underscores the strategic value of transparency and accountability leading to an improvement of financial performance.

While carbon disclosure serves as a strategic resource enhancing transparency and serving as a competitive advantage, on the other hand, when a company does not engage in carbon disclosure practices, it increases information asymmetry, which influences investor behaviour and market reactions significantly. Non-disclosure could lead to potential adverse selection problems if only good performing companies disclose their carbon information. This can lead to penalties for non-disclosing companies by investors, assuming inferior performance of non-disclosing companies (Matsumura et al., 2014). In addition, non-disclosure could potentially lead to increased transaction costs, driven by the need for extensive research to obtain information about a firm's probable emissions, mostly used for risk and company evaluation. Information asymmetry would increase costs for the investor, which would ultimately lead to increased costs for the firm, putting pressure on its profitability (He et al., 2013). Therefore, decreasing information asymmetry between stakeholders through carbon disclosure is expected to increase the financial performance of a firm.

This is in line with signaling theory, which states that carbon disclosure can help to reduce pressure from stakeholders, while enhancing a firm's legitimacy, and support from stakeholders, leading to improvement of financial performance (Hahn et al., 2015). Companies potentially enhance their image and reputation through carbon disclosure which immediately reduces the risk of value destroying stakeholder or pressure group activism. Moreover, positive carbon disclosure could lead to increased customer loyalty, thereby reducing customers' price elasticity for demand, especially among those who perceive carbon as a negative component of firm value. Besides, "climate-conscious" customers prefer to be associated with a company that is transparent about their carbon emissions, that is credible, and that can claim to be innovative in addressing climate change (Downar et al., 2021).

Conversely, low quality or dishonest carbon disclosure could lead to illiquidity, as negatively affected investors may become less willing to trade. Which increases the transactions costs and bid-ask spread, resulting in an increasement of required rate of return, detrimental to future market performance (Verrecchia, 2001; He et al., 2013). Besides, firms could potentially be penalized by stakeholders or institutions if the disclosed information does not add up to their expectations. Some information could be used against firms in carbon-intensive industries as justification to investigate the firm, leading to higher legal and compliance costs. Additionally, reputational damage due to activism and stakeholder pressure as a result of low-quality carbon disclosure could also negatively affect the future market performance of a firm (Matsumura et al., 2014).

The theoretical theory underpins a mostly positive effect of carbon disclosure on financial performance but addresses the challenges of carbon disclosure. According to theories like the RBV, signaling theory, and information asymmetry, carbon disclosure could significantly impact a firm's financial performance by enhancing transparency and accountability which could lead to increased investor trust, customer loyalty, and competitive advantage. Conversely, poor quality or dishonest disclosure may lead to adverse effects, including increased transaction costs, reputational damage, and potential legal costs, ultimately having a negative effect on a firm's financial performance.

3.1.2 Empirical insights

The previous empirical studies about the effect of carbon disclosure on financial performance are in line with the theory and predominately show a positive association. Alsaifi et al. (2020) studied a substantial period of 2007 to 2015, covering 977-firm year observations of companies listed on the London stock exchange. The paper combined 10 variables to create a financial performance index, and used a carbon disclosure score, derived from on a questionary by the CDP, as a proxy for carbon disclosure. The results indicate that for optimal resource allocation, like cost savings and operational advantages, companies should actively incorporate carbon mitigation in their business policies and need to ensure superior carbon disclosure. The outcome suggests that companies who consistently participate in voluntary carbon disclosure regarding their carbon practices, both achieve high financial performance and a long-term competitive advantage.

Matsumura et al. (2014) examined the effect of carbon emission disclosure on firm value after correcting for self-selection bias by incorporating systematic firm- and industry-level characteristics. They studied voluntary disclosed carbon emissions from period of 2006 to 2008. The study finds that investors incorporate a firm's transparency into its valuation, identifying a higher median market value for firms that disclose their GHG emissions compared to those that do not. Explained by the fact that stakeholders penalize high emitting firms or non-disclosing firms, highlighting the importance of not only carbon disclosure, but good carbon disclosure.

Griffin et al. (2017) researched if stock investors consider carbon disclosure as significant for the valuation of a firm, to rephrase, the effect of voluntary carbon disclosure on stock price performance. Like Matsumara et al. (2014), they found that investors consider GHG disclosure when evaluating a company. Moreover, did they find a significant stock market reaction to carbon disclosure. The response is negative if the level of carbon emissions is higher than expected, this reaction tends to be more negative for carbon-intensive industries. Therefore, the coefficient depends on the level of GHG emissions and the expected benchmark in the industry. Saka and Oshika (2014) studied a sample of 1,094 Japanese firm year observations in the period of 2006 to 2008 by applying Ohlson model. They found a positive effect of carbon disclosure on company value. Like Griffin et al. (2017), this effect tends to be higher with the level of GHG emissions. He et al. (2013) used a simultaneous equations model to study the effect of carbon disclosure on the cost of capital as a proxy for financial performance. They examined 181 firms in the years 2009 and 2010 and found a negative relationship, which implies a positive relationship between carbon disclosure and company value. The study highlights the importance of stakeholder demand for suitable carbon disclosure. Kurnia et al. (2020) used structural equation modelling to study the effect of GHG disclosure on financial performance and firm value for mining, manufacturing, and agriculture companies in Indonesia. The results suggest that carbon disclosure functions as an indicator of a firm's potential to enhance its future performance through green initiatives.

Although the previously mentioned literature predominantly underscores the positive effect of carbon disclosure on financial performance some studies are more sceptical, underlying different challenges associated with carbon disclosure. Sullivan & Gouldson (2012) have found opposing results to the previous literature. The financial incentives for carbon disclosure have been substantially overestimated, according to the researchers, voluntary disclosure does not satisfy investors. Companies are urged to disclosure carbon emissions at the cost of the quality of the reported information. Resulting in a lack of necessary quality of corporate reporting on climate change for investors to conduct a meaningful comparison between different companies.

Lu et al. (2021) studied the effect of carbon disclosure on financial performance by analysing Fortune 500 companies using CDP data in the period from 2011 to 2018. They utilized a content analysis method, guided by PwC, to create a carbon disclosure index score as a proxy for carbon disclosure. Return on assets (ROA) is used as a proxy for financial performance. They find that firms in carbon-intensive industries are not able to improve the financial performance through carbon disclosure in the short-term. However, carbon disclosure contributes significantly to non-carbon-intensive industries to the enhancement of financial performance in the short-term and long-term.

Siddique et al. (2021) studied the 500 largest worldwide firms based on the financial times global 500, over the period of 2011 to 2015. They used a carbon disclosure score derived by the CDP as a proxy for carbon disclosure and used ROA and Tobin's Q as a proxy for short-term and long-term financial performance, respectively. The study finds a negative effect of carbon disclosure on financial performance in the short-term, but positive in the long-term. The short-term negative effect is explained by the fact that financial costs for carbon disclosure outweigh the benefits in the short-term. A long-term positive effect shows that companies improve their financial performance when carbon disclosure is increased. The use of Tobin's Q as a proxy emphasizes investor's positive perception of carbon disclosure in the long-term.

3.1.3 Hypotheses

Two hypotheses have been developed to investigate the relationship between carbon disclosure and financial performance utilizing the theoretical framework and empirical background. Disclosure of carbon-related information is not merely a matter of transparency but has far reaching implications for the financial performance of a company as evidenced in the previous.

Research and theory highlight the significant impact of carbon disclosure on a firm's short-term financial performance. In line with the studies from Alsaifi et al. (2020), Matsumura et al. (2014), Saka and Oshika (2014), and Griffin et al. (2017) supporting the positive effect of carbon disclosure on financial performance. Keeping in mind the negative short-term effect explanation of Siddique et al. (2021) as a result of increased short-term cost. However, this study expects, in line with theory, that the short-term benefits outweigh the short-term costs. Following the line of thought of RBV theory where disclosure acts as a strategic resource, enhancing transparency and accountability, which in turn reduces information asymmetry and positively influences investor behaviour and market perception. Following the signaling theory, carbon disclosure immediately impacts a company's image and reputation. Where superior carbon disclosure combined with effective carbon mitigation strategies result in optimal resource allocation and higher financial performance. Therefore, it can be hypothesized that:

H1: *A positive relationship exists between carbon disclosure and financial performance in the short-term.*

In the long-term, the benefits of carbon disclosure extend further, influencing the financial performance of a firm positively. Over time, consistent and high-quality carbon disclosure yields a credible image among stakeholders and contributes to sustained financial health and market performance. This ongoing transparency helps in mitigating the risks associated with stakeholder activism and the reputational damage potential.

Especially in the long-term could positive carbon disclosure lead to increased customer loyalty. Following empirical studies, effects of carbon disclosure on financial performance also appear positive but with nuanced implications. Siddique et al. (2021) observed that although carbon disclosure may initially lead to a decline of financial performance due to short-term costs, it ultimately enhances financial performance over the long-term. Caused by sustained quality disclosure, building investor trust and market reputation, leading to increased firm value. Lu et al. (2021) highlight that while carbon disclosure might not immediately benefit carbon-intensive industries, it significantly boosts performance in non-carbon-intensive sectors in both short and long-term. These findings are consistent with the notion that carbon disclosure, as part of a long-term strategy, can lead to sustainable competitive advantage and financial growth. Consequently, does this lead to the second hypothesis:

H2: *A positive relationship exists between carbon disclosure and financial performance in the long-term.*

3.2 Carbon performance and financial performance

3.2.1 The underlying dynamics and principles

The financial performance of a firm is ambiguously influenced by carbon performance as well. Busch and Hoffmann (2011) discuss two theoretical aspects on the effect of carbon performance on financial performance, competitive advantage, and instrumental stakeholder theory. The first considers improvement of carbon performance as a way to simultaneously improve a firm's financial performance by creating a cost-based ecological advantage. As explained by Porter (1980) is the least-costs strategy one of the three ways to enhance your competitive advantage. Firstly, a firm can improve its carbon performance by reducing true economic costs while increasing the economic value of products resulting in direct cost reduction and an improvement of financial performance. Secondly, a firm could also leverage high carbon performance with differentiation of sustainable products to increase premiums on customer prices (Orsato, 2006). This is in line with the RBV theory and triple bottom line (TBL) theory. Both theories emphasize the importance of environmental aspects of the business. The RBV theory like mentioned before considers a firms' tangible and intangible resources as essential capabilities to establish a competitive advantage. Acknowledging that resources alone are not sufficient to establish a competitive advantage, specific strategies are necessary to leverage a firms' capabilities to gain a competitive advantage (Lee & Min, 2015). Moreover, the natural-resource-based view (NRBV) theory specifically addresses environmental resources as fundamental to establish a long-term competitive advantage. If a firm is able shift its focus from short-term resources to long-term environmental strategies, by acquiring organizational knowledge, incorporating stakeholders, and leveraging new (green) capabilities to enhance its environmental performance, it can establish a long-term competitive advantage (Hart & Dowell, 2011). This results in a positive effect on the financial performance of a firm. The TBL theory emphasizes that a company should not only consider its financial bottom line but should also consider its social and environmental bottom line (Elkington, 1997). The TBL theory encourages organizations to align their strategies with environmental stewardship, social governance, and economic development, creating a holistic and sustainable view on corporate strategies (Isil & Hernke, 2017). This theory contributes to the long-term competitive advantage strategy described in the NRBV theory.

The second theory of Busch and Hoffmann (2011) addresses stakeholder theory and is similar to the previously explained carbon disclosure theory. Stakeholders are key contributors to the financial performance of a firm. Within the same line of thought as the competitive advantage theory, can cost reduction through improvement of carbon performance be seen by stakeholders as a risk reducing measure. The carbon intensity of a firm is interpreted by investors as emission risk and improving someone's carbon performance results in lower risk premiums (Bolton & Kacperczyk, 2021). Improvement of carbon performance could also reduce employee retention and increase attraction resulting in higher productivity (Khurshid & Darzi, 2016). Moreover, a firm could enter various sustainability-focused financial markets and thereby addressing environmentally conscious investors when it significantly improves its carbon performance relative to his previous performance.

On the other hand, some argue that an investment in carbon performance can be seen as waste of resources because of the uncertainty of the expected pay-off. An investment in carbon performance as beforementioned are capital intensive, e.g. increase energy efficiency through innovations or transition to low-carbon emission products and processes, which put negative pressure on a firm's financial performance in the short-term. Linking to the trade-off theory of Friedman (1970) stating that environmental considerations lower a firm's financial performance because the financial benefits don't out weight the costs. This is partly explained because a firm would move resources away from his familiar core business, creating a potential disadvantage relative to non-environmentally accountable competitors. Especially in countries where carbon emissions are not internalized in the regulatory system, firms are not faced with regulatory punishment for emitting carbon and this increases the disadvantages compared to competitors (Misani & Pogutz, 2015). Adverse selection problems are also influencing the effect in the form of managerial optimism (King & Lenox, 2001). Explaining when managerial compensation is tied to short-term shareholder value, managers prioritize actions that maximize short-term profits. Creating an incentive to reduce environmental expenditures to boost profits when short-term shareholder value is high and conversely increase environmental expenditures when short-term shareholder value is low to shift attention away from financial performance (Schaltegger & Synnestvedt, 2002).

A possible combination of the theories results in a non-linear relationship between carbon performance and financial performance. Explained by the law of diminishing marginal returns when the marginal costs of an improvement exceed the marginal benefit. The effect of an extra carbon performance improvement decreases per improvement if from the same size, showing an inverted U-shaped relationship. Explained partly by early “low hanging fruit” improvements and the saturation of market response to a carbon performance improvement especially if competitors adopt similar sustainability measures (Brammer & Millington, 2008).

The effect of carbon performance on financial performance can therefore be seen as intricate. Initially carbon performance can be utilized as an ecological cost-based competitive advantage and product differentiator by leveraging firm capabilities in combination with long-term strategies. Combined with, perceived risk reduction, reduction of employee retention and attraction of sustainability-conscious investors. In the contrary can it be seen as a waste of resources, especially under regulatory pressure and vulnerable to adverse selection problems. A combination of the theories results in a convex-shaped relationship explained by the law of diminishing marginal returns.

3.2.2 Empirical insights

Prior research is in line with the theoretical background. Most studies find predominately mixed results. When a linear relationship is analysed, most studies lean towards a more significantly positive effect. Conversely, in studies examining a non-linear relationship, there is a predominately multifaced relationship between carbon performance on financial performance, caused by differences in time frames and other systematic effects.

Nishitani and Kobubu (2012) studied mandatory GHG emissions of 641 Japanese manufacturing firms in 2009. They examined the effect of GHG reduction, captured by a firm’s carbon intensity as a proxy for carbon dioxide productivity together with market dynamics in the form of market discipline, on firm value quantified by Tobin’s Q. They find that the improvement of a firm's carbon productivity by the reduction of GHG emissions, imposed by strong market discipline of investors/stakeholders, increases firm value. More importantly, they find that GHG reduction as a business strategy does not interfere with the economic incentives of a firm, therefore result in an increasement of economic performance.

Trinks et al. (2020) studied 1,572 international firms over the period of 2009-2017 and examined the effect of carbon efficiency on financial performance focusing on the resource efficiency of firms and the perceived systematic risk. They find that carbon efficiency is positively associated with financial performance, due to increased short-term operational performance, and negatively associated with perceived systematic risk, suggesting a valuable contribution to both a firm's operational and management risk.

On the contrary, Rokhmawati et al. (2015) and Rokhmawati et al. (2017) find a negative effect of carbon performance on ROA and on ROS, respectively. Both using the same initial sample size of listed manufacturing firms in Indonesia and the explanation is somewhat similar as well, namely understated government compensation and regulatory punishment, in line with Friedman's trade-off theory. They find a positive effect of carbon emissions (negative on carbon performance) on a firm's financial performance because the government compensation does not offset the additional costs to reduce GHG emissions and because firms do not receive sufficient penalties for GHG emissions.

As previously stated, most studies find a multifaced relationship or mixed results. Busch and Hoffmann (2011) employed a questionnaire, besides the uses of GHG emission data, to differentiate between carbon emission intensity as an outcome-based measurement and carbon management score as a processed-based measurement. They performed an ordinary leased squared (OLS) regression, and the findings show a positive relationship between outcome-based carbon performance and financial performance, and a negative relationship between process-based carbon performance and financial performance. The results suggest that direct achievements in carbon reduction enhance a company's financial performance due to efficiencies and market approval, conversely the overheads and complexities of implementing carbon management processes might outweigh immediate financial benefits, leading to a negative impact. Surprisingly, they only find a significant effect of outcome-based carbon performance on Tobin's Q, as proxy for financial performance, in contrast to ROA. Highlighting the fact that the influence of stakeholders, seen as long-term intangible value, may hold greater significance than the short-term efficiency of assets.

Trumpp and Guenther (2017) studied a sample of 2,361 firm-years in the period of 2008 to 2012 by analysing a regression model expressed in a quadratic form while differentiating between profitability and stock-market performance. They find significantly opposing coefficients for the relationship between carbon performance and financial performance. Being negative for the linear term and positive for the quadratic term, which is evidence for a U-shaped relationship. Concluding that carbon performance has a positive effect on financial performance after surpassing a minimum carbon performance level, while exhibiting a negative effect below that minimum. This could also be expressed as a negative short-term effect followed by a long-term positive effect.

Delmas et al. (2015) studied the short and long-term effect of carbon performance on financial performance using a panel dataset of 1,095 companies from 2004 until 2008. Similarly, to this study, they utilize ROA as a short-term measurement and Tobin's Q as a long-term measurement. They find a negative association in the short-term and a positive association in the long-term. The findings indicate that carbon performance improvements may not lead to short-term profitability. However, in the long-term, the market acknowledges the benefits of reduced emissions, and thereby increasing the financial performance.

Lewandowski (2017) applied non-linear econometric modelling techniques to investigate the effect of carbon performance on financial performance differentiating between annual reported carbon emission equivalent and improvements of carbon performance over a period. He examines a notably extended period from 2003 to 2015, focusing on a dataset encompassing 1,640 international companies. Like Trumpp and Guenther, he finds evidence for a U-shaped relationship where initially the relationship exhibits a negative trend, which subsequently transitions into a positive one. Explicitly, does it show a threshold effect for a level of carbon performance, where mitigation or improvements of performance only yield financial benefits after surpassing a certain level of carbon performance. Indicating a positive relationship for firms exhibiting superior carbon performance, contrasted by a negative relationship for firms with inferior carbon performance. More specifically, the effect on Tobin's Q exhibits a negative coefficient and on ROS a positive coefficient. The evidence suggests that while enhancements in carbon performance may elevate profitability, they simultaneously incur penalties by investors.

Misani and Pogutz (2015) research resembles the study of Busch and Hoffmann, and also examines the effect of different outcome and process measurements of environmental performance on the financial performance of a firm, proxied by Tobin's Q. Like Busch and Hoffmann, they use carbon intensity as an outcome measure, which serves as a proxy for a firm's carbon performance. However, they use an environmental performance score as processed-based measure. Similar to Trumpp and Guenther, the study includes a quadratic term, but the results are exactly opposite. Unlike Lewandowski, and Trumpp and Guenther, they find a positive linear term coefficient and a negative quadratic term coefficient, signifying an inverse U-shaped. In other words, attempts to enhance carbon performance can increase a firm's financial performance. However, as carbon performance increases further, this trend reaches a turning point where the economic costs start to outweigh the additional benefits, resulting in a negative effect on financial performance.

3.2.3 Hypotheses

Two hypotheses have been developed to investigate the relationship between carbon performance and financial performance utilizing the theoretical framework and empirical background.

The third hypothesis is supported by the competitive advantage theory of Busch and Hoffman (2011). Which explains that an improvement of carbon performance can lead to economic benefits such as cost reductions through more efficient operations and enhanced product value, aligning with Porter's least-cost strategy. However, following the reasoning of prior empirical research, an initial investment in carbon performance does not always yield immediate financial gains in the short-term due to the capital-intensive nature of such investments, supported by Friedman's trade-off theory. This study is in line with the reasoning of Trumpp and Guenther (2017), who found a minimum level of carbon performance before financial benefits can be reaped. "Too-little-of-a-good-thing" effect indicates that initial investments might have negative effect until a certain threshold, as evidenced by Lewandowski (2017), followed by a positive shift in financial performance. Hence, the following alternative hypothesis is constructed:

H3: *In the short-term, an U-shaped relationship between carbon performance and financial performance will offer a superior fit to a linear relationship.*

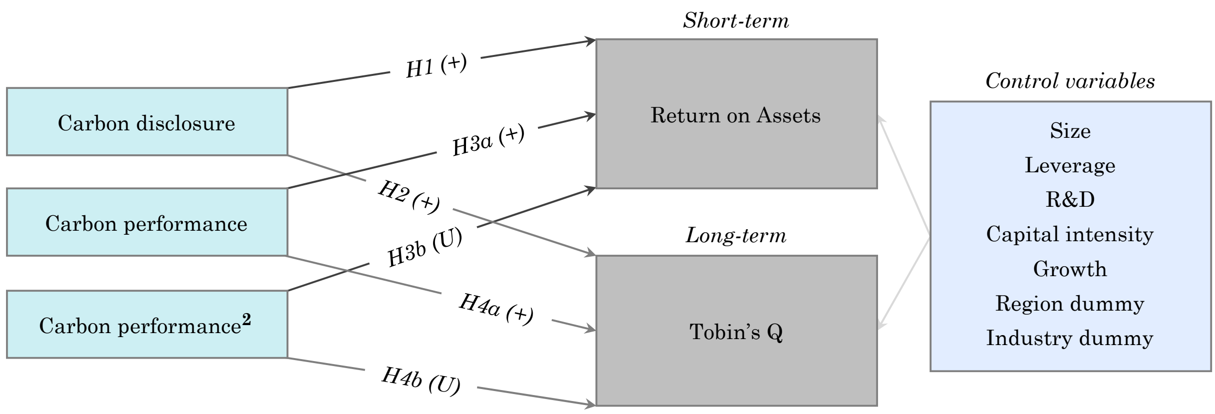
In the long-term, the positive relationship can be underpinned by the NRBV and TBL theories outlined by Hart & Dowell (2011). As firms transition from short-term resource allocation to long-term environmental strategies, by enhancing organizational knowledge, increased stakeholder integration and utilizing new capabilities, it can establish a long-term sustainable competitive advantage. Firms may reap initial financial benefits until some point by addressing low-hanging fruits in carbon performance, which are often less capital-intensive and exhibit fast returns on investment. However, beyond a certain point of carbon performance improvement, the economic marginal costs begin to exceed the marginal benefits. This study follows the reasoning of Misani and Pogutz (2015), who's finding illustrate diminishing marginal returns on the long-term after some point. This is supported by the findings of Delmas et al. (2015), who find the same inverted U-shaped relationship. As a result, the following hypothesis is formulated:

H4: *In the long-term, an inverted U-shaped relationship between carbon performance and financial performance will offer a superior fit to a linear relationship.*

3.3 Conceptual model

The visualization represents an overview of the expected different relationships between the dependent and independent variables in this study. The control variables are also stated.

Figure 1: Visualization of conceptual model



4 Methodology

This section will outline the composition of the dataset and the research design used to test the hypotheses in this study. First, the sample selection process is explained. Secondly, this section will elaborate on the dependent, independent and control variables used in this study. Thirdly, statistics will describe the geographical and industry distribution of the sample. Fourthly, this section delves into the chosen regression technique. Further, this chapter will show some preliminary checks before discussing the specific models used to examine the hypotheses.

4.1 Sample selection

For this study, the final sample consists of 12,687 firm-year observations and 2,017 largest publicly listed companies worldwide. These companies are selected given their global public exposure based on their market capitalization, which is calculated as the stocks outstanding times the current stock price (Kothari et al., 2009) from the period 2014 up to 2023.

Carbon data is retrieved from the ESG Database from Refinitiv Eikon, which possesses one of the most extensive ESG datasets, covering over 80% of the global market cap (Refinitiv Eikon, 2023a). To bridge the gap between the demand for carbon data and the reported or available information, Eikon developed a Carbon Data & Estimates model that follows a four-step approach (Refinitiv Eikon, 2023b). Their carbon process starts by estimating a company's CO_2 emissions by analysing annual reports. If the data is up to date, no further action is needed. However, if not, a CO_2 estimation model is employed. If the model is unable to generate an estimate, the Energy model is then utilized. If that model fails to produce results, the Median model is applied to determine the emissions. This systematic approach ensures the most accurate emission data set available. Furthermore, the financial data is retrieved from an Eikon database as well, to make sure that the methods for obtaining the variables are as closely aligned as possible. The company fundamentals dataset covers 99% of the global market capitalization for over 40 years of annual retrieved data (Refinitiv Eikon, 2023a).

The period 2014 until 2023 is chosen due to the recent escalating global focus on sustainability issues and significant regulatory changes on carbon emissions. The starting year, 2014, marks a critical turning point when many countries began implementing more rigorous carbon emission reporting standards, influenced by the Paris Agreement in 2015. By studying until 2023, this time frame not only allows for the observation of short-term impact but also enables an understanding of longer-term outcomes of carbon practices.

Firm-years with missing values and specific exclusions were deleted from the initial sample of 11,516 listed firms, and the final sample consists of 12,687 firm-year observations and 2,017 firms. The sample selection is summarized in Table 1. First, missing firm-year observations and datapoints with the value zero were excluded from the sample. Furthermore, the financial industry is, in line with previous literature on the effect of carbon disclosure or performance on financial performance (Busch et al., 2012; Jung et al. 2014; Delmas et al., 2015), excluded from the sample. Financial industry is defined by banks, banking, savings institutions, credit unions and other depository institutions according to the Standard Industrial Classification (SIC) codes (SICCODE, 2024). Some argue that the direct emissions of banks don't fully capture the carbon risk in their portfolios since these risks stem from the emissions on their financial assets, not their own operations. Others state that the financial sector, other than the non-financial sector, is restricted by unique regulations due to their potential significant impact on society, stemming from interconnection with the financial system. Finally, firms that were founded during the sample period were excluded from the sample due to a possible influence of abnormal variable behaviour around the entry and due to possible missing datapoints due to a limited time frame.

Table 1: Sample selection

The table provides a summary of the process followed to obtain the final sample of 12,687 firm-year observations of 2,017 firms. The numbers stated represent firm-year observations.

Selection	**Removed**	**Remaining**
Initial sample dataset		115,140
Missing datapoints and excluded if null[a]	101,004	14,136
Excluded financial industry	49	14,087
Excluded if founded during sample period	1,400	12,687
Final sample dataset		12,687

[a] Null values for the variable *Debt* were not excluded from the sample due to possible completely equity financed (unleveraged) firms. The significant drop of datapoints is explained by the limited availability of carbon disclosure (44,967 missing datapoints) and carbon performance (14,753 missing datapoints) data due to the lack of regulatory requirements or no prioritized reporting. The relatively small number of missing values of carbon performance, compared to carbon disclosure, are a result of the four-step Carbon Data & Estimates model of Eikon. Together with research & development data (20,292 missing datapoints) which is partly explained by the protection of intellectual property or strategic considerations. The missing values together explain around 78% of the total removed values.

4.2 Variables

4.2.1 Dependent variables

The dependent variable, financial performance, is measured, as previously mentioned, in both the short-term and long-term, and referred to as accounting-based and market-based measurements, respectively. In line with financial performance theory and prior empirical studies (Nishitani & Kokubu, 2012; Trinks et al., 2020; Rokhmatawati et al., 2015; Busch & Hoffmann, 2011; Delmas et al., 2015; Lewandowski, 2017; Misani & Pogutz. 2014), this study measures short-term financial performance using *ROA* and long-term financial performance using Tobin's Q (*Tobin's Q*) as dependent variable. The *ROA* is a widely used accounting-based measurement for financial performance and is calculated using the following formula (Eq. 1):

$$ROA_{i,t} = \frac{Net\ income_{i,t}}{\frac{(Total\ assets_{i,t} + Total\ assets_{i,t-1})}{2}} \quad (1)$$

ROA measures how effectively a company uses its assets to generate earnings for stakeholders. Which is particularly relevant when examining the impact of carbon disclosure and carbon performance, as these factors often involve significant asset intensity measures and investments (Delmas, 2015). Within the same argument, *ROA* is directly tied to a company's operational efficiency, unlike the return on equity (ROE), which is more prone to financing decisions and equity strategies. Contrarily, *ROA* provides a broader overview of a firm's profitability than return on sales (ROS), by encompassing both operational efficiency and asset utilization, while ROS only focuses on sales generated profit. The ROS is therefore a good reflection of the profitability of sales but lacks a broader view of financial implications of carbon strategies that involve significant asset management changes. Furthermore, *ROA* is a metric applicable to different firm types, regardless of their capital structure. ROE for example is significantly influenced by the financial leverage of a company, therefore less suitable in this empirical study comparing different kind of companies within different industries. ROS in the same way is useful when examining sectors where sales revenue is closely linked to environmental practices, but beyond that not suitable for different industry comparison. Which also results in the *ROA* being less vulnerable to financial manipulation. Especially compared to the ROE, which can be artificially boosted through increased leverage. Therefore, the *ROA* is the most comprehensive and relevant measure of financial performance in the short-term when studied in relationship to carbon disclosure and performance.

The other dependent variable used in this study is *Tobin's Q*. *Tobin's Q* is a forward-looking stock market performance indicator, and mostly used market-based measurement for financial performance. Especially in relationship with environmental variables, due to its function as an indicator of intangible value (Lewandowski, 2018). *Tobin's Q* reflects reputational impact, investor confidence, and perceived risk, therefore adequate for describing the corporate environmental performance (Guenster et al. 2011). Particularly relevant in this study, where international carbon emissions are not all internalized and priced, hence superior carbon performance could represent intangible value, signaling potential future growth. *Tobin's Q* represents the ratio of a firm's total market value to the total replacement value of its assets (Bartlett & Partnoy, 2020). *Tobin's Q* larger than 1 suggests a greater market value of a company's assets than the cost to replace them, where the difference represents the growth opportunities and value of intangible assets.

The formulation of the variable developed over a long period of time, starting with James Tobin in the late sixties, hereafter simplified and therefore made more practical by Kee Chung and Stephen Pruitt in 1994. Perfect and Wiles (1994) found that measurement errors are significantly lowered by using the "simplified" version of Chung and Pruitt's *Tobin's Q* as a dependent variable. Later in 1997, Steven Kaplan and Luigi Zingales published an updated version of the "simplified" *Tobin's Q*, which related more on the first formulation by Tobin. As stated by Barlett and Partnoy (2020), this definition "would shape the course of corporate governance research for the next two decades". *Tobin's Q* in this study is therefore calculated using the formula (Eq. 2) of Kaplan and Zingales (1997):

$$Tobin's\ Q_{i,t} = \frac{AT + MVE - BE - DT}{AT} \tag{2}$$

AT represents the total assets, MVE refers to common stock's market value, BE denotes the book value of equity, and DT stands deferred taxes on the balance sheet. Alternative market-based measurements are market-to-book value, abnormal stock returns or price-earnings (PE) ratio (Al-Matari et al., 2014). Both *Tobin's Q* and abnormal stock returns assume perfect information, which implies that all public information is incorporated into the stock price (Blose & Shieh, 1997). New information about for example carbon mitigation attempts will immediately be represented in the price. Abnormal stock returns can be useful for short-term studies but may not fully capture long-term value, because it only reflects current short-term price fluctuations. Contrarily, *Tobin's Q* reflects future growth expectations and sustained firm value, since it captures both tangible and intangible assets, representing a holistic view of a firm's market value. On the other side, market-to-book value also reflects market valuation but tends to focus more on tangible value of assets (Hulten & Hao, 2008). Therefore, less useful for this study on carbon disclosure and carbon performance. Lastly is PE ratio based on earnings, which can be vulnerable to accounting manipulation. In contrary, *Tobin's Q* is less prone to such influences because it is based on market value to asset's replacement costs. Hence, *Tobin's Q* is the most robust and appropriate measure for analysing the relationship of carbon disclosure and performance on long-term financial performance.

4.2.2 Independent variables

The first independent variable used in this study is carbon disclosure ($CD_{i,t}$). A proxy for carbon disclosure is retrieved from the ESG Database from Refinitiv Eikon, named emission score. It is an emission category score that quantifies a company's transparency and engagement in reporting its efforts and achievements in reducing environmental emissions across its production and operational processes, ranging from 0 to 1. It utilizes transparency simulation with applied weighting. Excluding immaterial information does not significantly impact a company's score. However, failing to report data points considered 'highly' material will significantly and negatively impact the company's score (Refinitiv Eikon, 2023b).

The other independent variables used in this study is carbon performance. In line with previous literature (Ott et al., 2017; Guenther et al., 2016; Gallego-Álvarez et al., 2014; Iwata & Okada, 2011; Busch & Hoffmann, 2011; Datt et al., 2019; Trumpp & Guenther, 2017; Lewandowski, 2017), this study utilizes *carbon intensity* (Eq. 3) as a measurement of carbon performance.

$$CI_{i,t} = \frac{\textit{Total GHG emissions}}{\textit{Total sales revenue}} \tag{3}$$

$CI_{i,t}$, describes the *carbon intensity* for a specific firm i in a given year t. *Total GHG emissions* represent the total scope 1 and 2 GHG emissions in tons and the *total sales revenue* represent a firm's total sales revenue in euros. While some studies (Matsumura et al., 2014; Lu et al, 2021; Delmas et al., 2015) include all three emission scopes in their analyses and some (Datt et al., 2019; He et al., 2013) focus solely on scope 1 emissions, this study, in line with the majority of the literature (Lewandowski, 2017; Misani & Pogutz, 2015; Busch & Hoffmann, 2011; Trumpp and Guenther, 2015) will concentrate on scope 1 and scope 2 emissions. These two scopes prioritise emissions that are directly controlled or owned by the company, thereby ensuring more accurately measurable data and clear accountability. Because the scopes are directly linked to a firm's operations, they yield better insights into the environmental performance. In contrast, scope 3 emissions are the sum of all other indirect emissions, therefore pose significant measurement challenges for companies, leading to reduced data quality. Additionally, scope 3 emissions are subject to less regulations, as a consequence of their complex nature and measurement difficulties.

The variables carbon performance (Eq. 4) is constructed by taking the natural logarithm of carbon intensity to reduce skewness in the data, creating a more symmetric variable and closer to normal. Hereafter, the logarithmically transformed carbon intensity is multiplied by -1.

$$CP_{i,t} = -\ ln(CI_{i,t}) \tag{4}$$

This inversion creates a more logical interpretable variable, where lower values of carbon intensity, which indicate higher carbon efficiency and thus better performance, are converted into positive indications. Consequently, higher values now represent better carbon performance.

4.2.3 Control variables

In this study, seven control variables are used to account for potential confounding factors to isolate the effect of carbon disclosure and carbon performance on financial performance.

Size, or firm size, is calculated by taking the natural logarithm of total assets (Eq. 5). Two main arguments explain why a positive relationship is expected, being firm capabilities and public exposure. Firstly, larger firms tend to be more profitable than smaller firms (Hall & Weiss, 1967), because they tend to have more resources in place, which lowers their default probability (Lewandowski, 2017). This at the same time results in larger firms being more capable to invest in profitability enhancing technologies (Rokhmawati et al., 2015). Besides, larger firms might experience larger economies of scale and scope (Downar et al., 2021), hereby being more cost- and operationally efficient. On the other hand, the legitimacy and reputation of larger firms are more influenced by stakeholder attention, and therefore, show a higher level of social responsibility compared to smaller firms (Udayasankar, 2008). Resulting in higher scrutiny regarding their practices which can influence both their management strategies and impact on financial performance. Larger firms also experience more complex operations and organizational structures, leading to slower decision-making processes, increased bureaucracy, inflexibility, and low innovations (Thompson, 1965). This results in an ambiguous expected effect on a firm's financial performance.

$$Size_{i,t} = ln(AT) \tag{5}$$

Leverage is described in the literature (Kolk & Hoffmann, 2007; Trumpp & Guenther, 2017; Siddique et al., 2021; Iwata & Okada, 2011; Clarkson et al., 2008) as indicator of systematic firm risk and is calculated by dividing a firm's long-term total debt by total assets (Eq. 6). Leverage or risk, increases the likelihood of bankruptcy and creditor dependency, leading to degraded loan conditions. Therefore, is expected to have a negative effect on a firm's financial performance.

$$Leverage_{i,t} = \frac{TD}{AT} \tag{6}$$

Research & Development (R&D), or R&D intensity, is measured by dividing the total R&D expenses by total sales revenue (Eq. 7). The R&D intensity indicates a firm's capacity for innovation through knowledge expansion. McWilliams and Siegel (2000) highlight R&D as a critical determinant of financial performance, arguing that omitting R&D from empirical models can lead to misspecification. Despite this, empirical studies often exclude R&D due to data accessibility issues or to maintain larger sample sizes across diverse industries (Lewandowski, 2017). Misani and Pogutz (2015) show the importance of R&D as a control variable in understanding the relationship between environmental performance and financial performance. Studies often highlight the potentially long-term positive impacts on financial performance. However, it's also acknowledged that this investment in innovation can lead to short-term decreases, reflecting the initial costs and risks associated with R&D activities (Trumpp & Guenther, 2017). Therefore, in this study the effect on *ROA* is expected to be negative, but on *Tobin's Q* to be positive.

$$R\&D_{i,t} = \frac{R\&D\ expenditures}{Total\ sales\ revenue} \tag{7}$$

Capital intensity is often used in the literature (Delmas et al., 2015; Griffin et al., 2017; King & Lenox, 2022; Iwata & Okada, 2011; Busch et al., 2012; Wang et al., 2014) as indication for a company's strategy towards growth, measured as the ratio of total assets to sales revenue (Eq. 8) (Russo and Fouts, 1997). It shows the required capital that is needed for one dollar of revenue output. Thus, a capital-intensive company requires more assets to produce the same unit of output. Old machines or techniques could be an explanation for a higher capital intensity, which could make it more difficult to decrease GHG emissions. This could harm a firm's financial performance. However, environmental companies that invest in sustainable and energy-efficient technologies might find opportunities to boost their financial outcomes (Rokhmawati et al., 2017). Therefore, the effect is expected to be both negative and positive.

$$\text{Capital intensity}_{i,t} = \frac{AT}{\text{Total sales revenue}} \tag{8}$$

Growth, or sales growth, is measured as the yearly variation in sales revenue as a ratio of total sales revenue (Eq. 9). High growth could indicate a potential for additional returns through market penetration or product launches, which positively impact a firm's financial performance (King & Lenox, 2002; Wang et al., 2014). Therefore, a positive relationship is expected.

$$\text{Growth}_{i,t} = \frac{\text{Total sales revenue}_t - \text{Total sales revenue}_{t-1}}{\text{Total sale revenue}_{t-1}} \tag{9}$$

Region, indicating a dummy variable for different international regions, following the reasoning of Busch and Hoffmann (2011). Businesses operate within diverse institutional environments, each with its unique climate change regulations and schemes. The European Union (EU) operates under the EU ETS since 2005 (European Commission, 2015) and the Green Deal since 2019 aiming for carbon neutrality by 2050 (European Commission, 2019). In North America, the regulation varies per state, with California having its own cap-and-trad program (California Air Resources Board, 2013) and Canada with the Greenhouse Gas Pollution Pricing Act (Government of Canada, 2018). In Asia-Pacific, China launched the largest ETS in the world in 2021 (ICAP, 2021) and Australia utilizes the Emission Reduction Fund (ACCU scheme) to encourage voluntary participation from organizations and individuals to implement new reduction practices and technologies (Australian Government, 2015). Consequently, four categorical variables were introduced to represent the European Union, North America, Asia-Pacific, and rest of the global countries.

Finally, *industry*, a dummy variable is added as a control variable to differentiate between industries. Industry dummies are utilized to adjust for the specific features of each industry and are classified with 4-digit SIC codes, in line with other literature (Busch & Hoffmann, 2011; Downar et al., 2021; He, 2013; Clarkson et al., 2008). The industries are categorized in eight different industries: Agriculture, Forestry and Fishing (0100-0999), Mining (1000-1499), Construction (1500-1799), Heavy Manufacturing (2000-3499), Consumer Goods Manufacturing (3500-3499), Transportation and Utilities (4000-4999), Wholesale and retail trade (5000-5999), Real estate, Finance and Services (6500-8999).

4.3 Descriptive analyses

Table 2 presents the sample composition by year, region, and industry. Overall, you see an increase in total firm-year observation for both the industry and geography, showcasing the increasing importance of emission disclosure and availability of carbon data.

In terms of industry distribution per year, the *Heavy Manufacturing* and *Consumer Goods* manufacturing industries consistently dominate the dataset, with peak observations in 2022, contributing almost 38% and 36% to the total dataset, respectively. The notably high contribution of the manufacturing industry within the dataset, reflects the high presence of carbon management practices and disclosure of carbon emission data. The manufacturing industry represents an intensive carbon emission sector and may be under greater scrutiny from stakeholders and regulators. At the same time, the *Agriculture* sector maintains the lowest representation (0.64%) despite its critical role in the carbon cycle, and *Wholesale & Retail*, which directly interacts with customer demand for more sustainability, is also underrepresented (2.92%). The distributional differences highlight the important considerations of carbon management and impact of each sector. The results should be interpreted with caution, as findings could be influenced by the sectors that are overrepresented. Therefore, it is crucial to include the industry dummy variable in the regression analyses, to reduce potential sector specific biases.

The dataset reveals a diverse balanced geographical distribution, with 25% of the total 12,687 firm-year observations in the dataset from *Europe*, 21.5% from *North America*, 40.5% from *Asia-Pacific* and the resulting 13% from the *Rest of the World*. A significant share of the dataset is from *Asia-Pacific*, showcasing the growing prominence in the global market of that region. The region shows an accelerated increase after 2020 from 684 in 2020 to 823 in 2021 up to 934 in 2022, which is mostly caused by new regulations and the earlier mentioned ETS in 2021. Further, the *Europ*e region presents consistent observations over the years which may reflect its early and robust regulatory environment and its influence on the financial markets. The progressive growth in firms disclosing information on their carbon output corresponds with the earlier outlined theoretical framework, which posits a growing consciousness of sustainability issues over time. This increase could be beneficial for the study, offering a rich longitudinal perspective on the evolution of carbon practices and their financial implications. However, the decline in observations for 2023 across all regions, especially in *Europe*, may require attention as it could impact the robustness of conclusions.

Table 2: Sample description

Allocation of 12,687 firm-year observations across various industry sectors and geographical regions over a period from 2014 to 2023.

	Firm-year observations per year										
	2014	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Total**
Industry[a]											
Agriculture	2	2	5	7	12	12	13	15	16	7	91
Mining	33	31	33	40	45	51	52	55	54	10	404
Construction	27	31	32	36	40	44	47	56	56	11	380
Heavy Manufacturing	300	332	380	417	480	560	652	727	753	181	4,782
Consumer goods	287	314	336	396	458	550	639	715	709	125	4,529
Transport & Utilities	69	71	77	84	89	99	115	118	118	22	862
Wholesale & Retail	22	22	22	28	37	40	60	66	64	10	371
RE, Finance & Services	55	62	68	76	100	150	209	251	247	50	1,268
Total	**795**	**865**	**953**	**1,084**	**1,261**	**1,506**	**1,787**	**2,003**	**2,017**	**416**	**12,687**
Region[b]											
Europe	238	250	268	279	332	387	451	455	446	65	3,171
North America	162	188	211	241	275	358	413	463	379	35	2,725
Asia-Pacific	304	324	351	407	468	551	684	823	934	293	5,139
Rest-of-the-world	91	103	123	157	186	210	239	262	258	23	1,652
Total	**795**	**865**	**953**	**1,084**	**1,261**	**1,506**	**1,787**	**2,003**	**2,017**	**416**	**12,687**

[a] Agriculture, Forestry, and Fishing (0100-0999); Mining (1000-1499); Construction (1500-1799); Heavy Manufacturing (2000-3499); Consumer Goods Manufacturing (3500-3499); Transportation and Utilities (4000-4999); Wholesale and Retail Trade (5000-5999); Real Estate, Finance, and Services (6500-8999).

[b] Europe (Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, and United Kingdom); North America (Canada and United states); Asia-Pacific (Australia, China, Hong Kong, India, Indonesia, Japan, Kazakhstan, Malaysia, New Zealand, Philippines, Singapore, South Korea, Taiwan, Thailand, and Vietnam.

Table 3 displays the summary statistics for the variables in this empirical model, adjusted for distortions from outliers by winsorizing the lowest and highest percentiles of each variable (Table A.1). The natural logarithm of *Tobin's Q* is also stated, as this variable will be used as dependent variable in this study based on preliminary assessments.

The median first dependent variable in this sample, *ROA*, is 0.055, or 5.5%, indicating that firms on average generate a moderate return on their assets, with a slightly higher average mean of 6.3% influenced by outliers. The standard deviation of 0.06 indicates a relatively uniform performance in the sample, but the range from -6.4% to 20.1% reveals the variability between the companies, highlighting the broader range of financial health and performance strategies within the sample. The other dependent variable, unwinsorized *Tobin's Q*, has a significantly higher mean than its median, which, along with a high standard deviation, suggests that the valuations based on the long-term performance vary widely, with some companies showcasing exceptionally high long-term relative market performance. The unreasonably high maximum outliers up to 61.168 far above the mean of 1.846 in the sample could be explained by companies whose market values are highly inflated either due to speculative factors, market perceptions of their growth potential, or possibly accounting deviations that are not reflected in the book value of their assets. For instance, companies with significant intangible assets such as patents, brand value, or innovative technologies might not have these factors fully accounted for in their book value, leading to a higher *Tobin's Q*. The transformed, *Ln Tobin's Q*, indicates a much lower difference between the mean and the median, and reveals a more normalized distribution.

The control variable *CD* reveals a median very close to its mean with a relatively large standard deviation. The minimum and maximum values show that the variable acts like an index, ranging from 0.001 until 0.999. A higher value indicates a wider range of carbon disclosure practices on multiple levels in the company. The other control variable *CP* has a median close to its mean, though with a considerable standard deviation and a wide range between the minimum and maximum values, indicating differences between the carbon performances of companies in the sample. The squared term of carbon performance could reveal non-linear effects in the model, with a much higher mean and maximum, highlighting the influence of outliers in the sample.

The control variable *Size*, with a mean of 17.648, a close median of 17.371 and a standard deviation of 2.768, shows a symmetry around the median values with a normalized distribution. This suggests that the average size is representative of the typical firm in the sample. The average *Leverage* value of the companies in the sample is around 24%, suggesting conservative debt levels with some upper outliers, 69.9%, showcasing high debt burdens and some lower outliers, 0%, revealing a 100% equity finance strategy. The *R&D intensity* with a mean o 4.6% with a small standard deviation implies consistent, but modest investment behaviour across the sample, with some companies in the sample revealing a minimum value of zero, indicating no investments in R&D at all. The *Capital intensity* shows moderate variability, and the year-on-year *Growth* is on average 9.2% in the company, which suggest a robust growth rate overall in the sample, though the negative minimum reveals some companies in the sample that experience contraction.

Table 3: Summary statistics

Summary statistics for the dependent, independent and control variables. The table shows the means, medians, standard deviations (SD), minimum- and maximum value and the number of firm-year observations of the variables in the sample.

	Mean	**Median**	**SD**	**Min**	**Max**	**N**
ROA	.063	.055	0.060	-.064	.201	12,687
Tobin's Q	1.846	1.195	2.307	.122	61.168	12,687
Ln Tobin's Q	.284	.178	0.725	-1.073	2.307	12,687
CD[a]	.653	.693	0.243	.001	.999	12,687
CP[b]	4.958	4.53	2.730	-1.176	12.54	12,687
CP^2	30.737	20.54	27.357	.042	93.552	12,687
Size	17.648	17.371	2.768	12.137	24.250	12,687
Leverage	.240	.230	0.162	0	.699	12,687
R&D intensity	.046	.021	0.070	0	.406	12,687
Capital intensity	1.704	1.362	1.198	.442	7.954	12,687
Growth	.092	.062	0.193	-.294	.750	12,687

[a] Carbon disclosure, an emission category score that quantifies a company's transparency and engagement in reporting its efforts and achievements in reducing environmental emissions across its production and operational processes. [b] Carbon performance is measured by taking the negative natural logarithm of carbon intensity.

4.4 Preliminary assessment

Before selecting and specifying the most suitable model for hypothesis testing, preliminary assessments were conducted to examine the data for linearity between the dependent and independent variables, and multicollinearity between independent variables. After choosing the model, tests for homoscedasticity of error terms and normality of the residuals were performed. Assessing some of these criteria before choosing the appropriate model is essential and considered best practice in empirical studies (Yang et al., 2019).

Linearity between the dependent and independent variables is tested based on scatter plots of residuals. The residuals are plotted on the y-axis against the predicted values on the x-axis, which visualizes the relationship, shown in Figure A.1 (Osborne & Waters, 2019). The residuals in all plots are randomly scattered around the horizontal zero axis across the range of predicted values, which suggests homoskedasticity. As expected, the regressions that include carbon disclosure exhibit a ceiling effect, explained by the index character of the variable ranging from 0 until 1. Furthermore, the plots don't show a clear pattern, such as a funnel or curvilinear shape. This supports the linearity assumption for this model.

Outliers and the distribution of the variables in this study are graphically tested using box plots. Some significant outliers are detected, therefore the lowest and highest percentiles of each variable are winsorized. Winsorization is a statistical technique used to minimize the influence of outliers in a dataset, which is achieved by replacing the extreme in the distribution with values closer to the median (Tukey & McLaughlin, 1963). This method ensures central tendency and variability metrics are not disproportionately affected by outliers. It involves replacing the extreme values—both the highest and lowest—beyond a certain percentile with the closest values within the threshold. For example, in a 90% winsorization, data above the 95th percentile and below the 5th percentile are replaced with the values at those percentiles. This process reduces the impact of outliers without completely discarding them, preserving the overall data structure. Table A.1 describes the variable before and after winsorization. The effect of this process can be seen in the data, as the standard deviation (SD) decreases for most variables after Winsorization, reflecting a reduction in variability due to extreme values. The minimum and maximum values for each variable are also closer to the mean, which suggests that Winsorization reduces the influence of extreme data points on the analysis. Figure A.2 and Figure A.3, show the distribution and outliers of the dependent and independent variable after winsorizing, respectively.

Normality assumption assumes that the residuals of the regression model are normally distributed. The residuals show the differences between the observed values of the dependent variable and the values predicted by the model. Many regression models that statistically test the significant of coefficients rely on assumption of normal distribution. First, a Q-Q plot is used to visually test for normality, which compares the quantiles of the dataset against those of a normal distribution. In a normal Q-Q plot, data plotted against normal quantiles should align with a straight diagonal line, deviation from this line indicates skewness (Das & Imon, 2016). Figure A.4 shows a somewhat linear distribution for all models, especially around the centre, but also some deviations around the tale. In all four plots, the residuals at the lower and upper ends deviate from the reference line and suggests heavier tails than the normal distribution, which indicates presence of some outliers. Although, around the mean, the points move more closely to the line, indicating that the larger part of the data is normally distributed. Based on the Q-Q plot the residuals are somewhat normally distributed. Schmidt and Finan (2018) argues that in large sample sizes, the assumption of normally distributed residuals may not significantly impact the validity of regression results, thus questioning the necessity of transforming outcomes. Therefore, the somewhat normality assumption is enough to proceed with the regression analysis without necessitating significant data transformation, particularly given the large sample size that tends to mitigate the effects of non-normality on the regression results.

Multicollinearity is present in the sample when interdependency exists among explanatory variables within the model. This can undermine the structural integrity of regression analyses, leading to issues with accuracy of the model parameters (Farrar & Glauber, 1967). If independent variables are highly correlated with each other, a multicollinearity problem exists. Multicollinearity is tested based on two different assessments. Multicollinearity is first tested with the Pearson correlation matrix, shown by Table A.2. The Pearson correlation matrix shows the correlation coefficients and significance levels for the dependent, independent, and control variables. The Pearson correlation shows a negligible relationship between the carbon disclosure and the *ROA* (r = 0.018), and a small negative relationship with the *Ln Tobin's Q* (r = -0.116). Carbon performance and it's squared term show a weak positive association with both *ROA* and *Ln Tobin's Q*. *Size* and *Leverage* are negatively correlated with both the dependent variables, indicating that larger and more leveraged firms may have lower profitability in the short and long-term. Interestingly, *R&D intensity*, while negatively correlated with *ROA* (r = -0.080), it shows a strong positive relationship with *Ln Tobin's Q* (r = 0.342).

Growth exhibits a positive correlation with *ROA* (r = 0.241) and *Ln Tobin's Q* (r = 0.148). The negative correlation of *Capital intensity* with *ROA* (r = -0.227) and *Ln Tobin's Q* (r = -0.066) implies that firms with higher capital relative to revenue might less profitable. Most correlation coefficients are under 0.5, therefore the dataset appears to have a low risk of multicollinearity. Although there might be a risk of multicollinearity, particularly between variables such as *Ln Tobin's Q* and *Size*, which could influence the reliability of regression coefficients if used together in a predictive model. To ensure absence of multicollinearity in the analyses, it is further tested based on the Variance Inflation Factor (VIF) scores. VIF scores show the extent to which independent variables are linearly correlated with one another. According to Kim (2019), multicollinearity needs further examination when the VIF score is greater than 5 and is problematic when its higher than 10. Table A.3 shows that all variables, when the squared term of *CP* is excluded, fall below the critical threshold of 5. Consequently, based on the results from both the Pearson correlation and VIF evaluation multicollinearity is not present among the variables in this study.

4.5 Model specification

This section will include comprehensive considerations leading to the appropriate technique to answer the research question and analyse the dataset appropriately to its characteristics. Beginning with the characteristics of the variables in this study, followed by an examination of the relationship between the independent variables and the dependent variable. Furthermore, the panel data nature of the dataset determines the model choice and complementary aspects are briefly discussed. Subsequently, various panel data options are considered. This section ends with the different models used to test the hypotheses, which will answer the research question.

Given the numerical and continuous nature of both the dependent and independent variables, regression analysis serves as the statistical approach for evaluating the hypotheses in this paper. Based on the preliminary assessment, the relationships between the dependent and independent variables are expected to be somewhat linear, the residuals are somewhat normally distributed, and multicollinearity does not exist in the sample. Later, in additional assessments, the presence of heteroskedasticity and serial correlation is not excluded from this study, therefore robust clustered standard errors are added to account for these biases. A multiple linear regression model is most suitable in this study, which is a direct extension of a simple linear regression. It includes multiple regressors to allow for an examination of the simultaneous effect of multiple factors on an outcome variable (Montgomery, 2021). However, using only a simple multiple linear regression model to study the impact of carbon performance on financial performance might be insufficient to capture the intricate relationship, due to a probable U-shaped relationship between the variables. Therefore, a polynomial multiple regression, in line with previous literature, is also applied in this research (Lewandowski, 2017; Trumpp and Guenther, 2015). A polynomial regression is a specific form of multiple linear regression, where the dependent variable is modelled using the kth powers of independent variables, allowing to capture non-linear relationships as well (Ostertagová, 2012).

Building further on multiple and polynomial regression analysis, it’s important to consider how these methodologies intersect with the use of panel data in econometrics. Longitudinal data, also known as panel data, consists of measurements from N cross-sectional units (for example, companies) across T time periods. By leveraging variation along both of these dimensions, panel data analysis is regarded as an exceptionally effective method for analysing data (Chamberlain, 1984). The combination of linear and polynomial multiple regression techniques with panel data enables this study to gain a deeper understanding of complex relationships over time and across different entities.

Their complementary relationship allows for more complex multiple regressions, control for unobserved heterogeneity, and could yield more statistically significant results due to the increased number of observations that arise from combining information across entities and time periods (Pesaran, 2015).

Pooled-, fixed effects- and random effects model are three estimation models to evaluate when analysing panel data. The pooled regression model considers each observation across individuals and years as independent, focusing solely on variations between observations without accounting for variations within individual observations (Baltagi, 2008). Unlike this study, a pooled regression model would be suitable under the assumption that individual units lack unique time-invariant characteristics that affect the variable of interest, or when the data itself could be considered cross-sectional, where time or individual characteristics are not the primary focus. As Bell and Jones (2015) explain, the fixed model assumes that something within a company may impact or bias the outcome variables and that this company-specific factor does not change over time. By focusing on within-company variations, the fixed effect model effectively controls for all time-invariant differences among the companies, thus providing a way to control for unobserved heterogeneity when this heterogeneity is constant over time. The random effects model, on the other hand, allows for variation both within and across companies. It assumes that the company-specific effect is a random variable that is uncorrelated with the predictor variables. In certain situations, random effects models may result in biased outcomes, although they decrease the variance in the estimates for coefficients. Conversely, fixed-effects models provide unbiased estimates but can suffer from significant reliance on the size of the sample, which might increase the estimates' variability. Therefore, some problems mentioned by Bell and Jones (2015) should be considered before choosing the appropriate random or fixed effect model.

High variance problem of a fixed-effect model estimate is especially the case when there is limited within-unit variability or small number of observations. This sensitivity to sample-specific noise leads to less reliable estimates. In the contrary, random-effect models provide more consistent estimates across different samples by averaging information and assuming a common variance component σ^2, which can cause estimates to regress towards the mean, particularly when there is few data. As for this study, the dataset provides a 10-year observation period per company, which lowers the likelihood of a high variance problem. Moreover, carbon disclosure and carbon performance variables vary significantly over time within companies, which both fixed- and random effect models can handle. However, the dependent financial performance variables don't change that much over time, which may not significantly impact within-company estimates. The within-company variation for the dependent variable is therefore limited, which is critical for a fixed effect model, and this increases the likelihood of a variance problem. The less dynamic nature of the financial performance variables also supports the assumption that the individual effects are uncorrelated with the explanatory variables. Based on the theoretical reasoning, the random-effect model is preferred.

Bias problem of random-effect model is a result of partial pooling, requiring no correlation between the interested covariate and the unit effect to avoid bias in the coefficient estimates. The problem is present when a relevant variable is omitted from the model, causing any correlation between the interested covariate and the unit effect to reflect omitted variable bias. The Hausman test, used to detect such violations, often fails to reject the null hypotheses due to insufficient power, implying bias in the coefficient estimates despite non-significant results. Despite potential bias, a random-effect estimator might still be preferred for its variance reduction capabilities, although the Hausman test does not address this trade-off. The bias introduced by potential correlation between the unit effect and the interested covariates weight out against the improved precision of the estimates from the partial pooling of information.

Concluding, based on theoretical reasoning, the random-effect multiple regression model is the most suitable model for this specific study. Despite the rejected null hypothesis of the random effect being the most suitable model for all models by the Hausman specification tests (Table A.4 & Table A.5).

4.6 Models

Hypothesis 1 examines the relationship between carbon disclosure and financial performance in the short-term. The regression formula (Eq. 11) for model 1 is presented as follows:

$$ROA_{i,t} = B_o + B_1 CD_{i,t} + B_2 Size_{i,t} + B_3 Leverage_{i,t} + B_4 R\&D_{i,t} + B_5 Capital\ intensity_{i,t} \\ + B_6 Growth_{i,t} + B_7 Region_i + B_9 Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \tag{10}$$

Hypothesis 2 examines the relationship between carbon disclosure and financial performance in the long-term. The regression formula (Eq. 12) for model 2 is presented as follows:

$$Ln\ Tobin's\ Q_{i,t} = B_o + B_1 CD_{i,t} + B_2 Size_{i,t} + B_3 Leverage_{i,t} + B_4 R\&D_{i,t} \\ + B_5 Capital\ intensity_{i,t} + B_6 Growth_{i,t} + B_7 Region_i \\ + B_9 Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \tag{11}$$

Hypothesis 3a examines a linear relationship between carbon performance and financial performance in the short-term. The regression formula (Eq. 13) for model 3 is presented as follows:

$$ROA_{i,t} = B_o + B_1 CP_{i,t} + B_2 Size_{i,t} + B_3 Leverage_{i,t} + B_4 R\&D_{i,t} + B_5 Capital\ intensity_{i,t} \\ + B_6 Growth_{i,t} + B_7 Region_i + B_9 Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \tag{12}$$

Hypothesis 3b examines a possible U-shaped relationship between carbon performance and financial performance in the short-term. The regression formula (Eq. 14) for model 4 is presented as follows:

$$ROA_{i,t} = B_o + B_1 CP_{i,t} + B_2 (CP_{i,t})^2 + B_3 Size_{i,t} + B_4 Leverage_{i,t} + B_5 R\&D_{i,t} \\ + B_6 Capital\ intensity_{i,t} + B_7 Growth_{i,t} + B_8 Region_i \\ + B_{10} Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \tag{13}$$

Hypothesis 4a examines a linear relationship between carbon performance and financial performance in the long-term. The regression formula (Eq. 15) for model 5 is presented as follows:

$$Ln\ Tobin's\ Q_{i,t} = B_o + B_1 CP_{i,t} + B_2 Size_{i,t} + B_3 Leverage_{i,t} + B_4 R\&D_{i,t} \\ + B_5 Capital\ intensity_{i,t} + B_6 Growth_{i,t} + B_7 Region_i \\ + B_9 Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \tag{14}$$

Hypothesis 4b examines a possible inverted U-shaped relationship between carbon performance and financial performance in the long-term. The regression formula (Eq. 16) for model 6 is presented as follows:

$$\begin{aligned} Ln\ Tobin's\ Q_{i,t} = \ & B_o + B_1 CP_{i,t} + B_2 (CP_{i,t})^2 + B_3\, Size_{i,t} + B_4\, Leverage_{i,t} + B_5\, R\&D_{i,t} \\ & + B_6\, Capital\ intensity_{i,t} + B_7\, Growth_{i,t} + B_8\, Region_i \qquad (15) \\ & + B_{10}\, Industry_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t} \end{aligned}$$

4.7 Additional assessment

After specifying the models used in this study, additional assessments were conducted to test the data on homoscedasticity of error terms and serial correlation.

Homoskedasticity refers to the condition where variances of the error term across all levels of the independent variable are consistent (Schmidt & Finan, 2018). Conversely, heteroscedasticity arises when the variances of the error term vary with different levels of the independent variable, which signals an unequal spread of the errors. Unlike the normality assumption, a heteroskedasticity problem could have a significant impact on the validity of the analyses irrespective of the sample size. The presence of homoskedasticity is tested with the Breusch-Pagan test. Breusch and Pagan (1979) follows a chi-square distribution and is derived from the explained sum of squares in an auxiliary regression. If the null hypothesis is rejected with a significance level of 1%, heteroskedasticity is present. The test rejects the null hypothesis for all models (H1: F = 131.660, Probability > F = 0.000; H2: F = 81.710, Probability > F = 0.000; H3a: F = 136.470, Probability > F = 0.000; H3b: F = 125.220, Probability > F = 0.000; H4a: F = 98.780, Probability > F = 0.000; H4b: F = 94.010, Probability > F = 0.000). This is a strong signal for heteroskedasticity at a 1% significance level, therefore, to address this problem, robust clustered standard errors are applied based on the companies.

Serial correlation, in the idiosyncratic error term of linear panel-data models could biase standard errors as well and reduce the efficiency of the results (Drukker, 2003). Therefore, it's crucial to detect serial correlation in panel-data models. The proposed test by Drukker that is most effective is the Wooldridge (2002) test for serial autocorrelation applicable to unbalanced panel data sets. The null hypothesis for the Wooldridge test assumes that there is no first-order autocorrelation in the panel data. The test rejects the null hypothesis for all models (H1: F = 97.789, Probability > F = 0.000; H2: F = 402.026, Probability > F = 0.000; H3a: F = 97.200, Probability > F = 0.000; H3b: F = 97.166, Probability > F = 0.000; H4a: F = 404.403, Probability > F = 0.000; H4b: F = 405.494, Probability > F = 0.000). This is a strong signal for serial correlation at a 1% significance level. To address this problem, a cross-sectional time-series regression model of Baltagi and Wu (1999) is applied, designed for analysing panel data, particularly when the error term follows a first-order autoregressive process. This approach assumes that the error for any observation is correlated with the error for the previous observation within the same panel, which is in line with the previously mentioned findings.

5 Results

The following section presents and examines the findings of this study. Table 4 and Table 5 present the results from the random effect multiple regression analyses on the effect of carbon disclosure and carbon performance on financial performance in the short and long-term, respectively. The different columns describe the beforementioned models to test the four hypotheses used to answer the research question.

Model a and *model b* only include the control variables to examine the effect of these variables on the dependent variable to make sure that these influences will be accounted for in the analyses that follow. The size of a company is negatively associated with ROA ($\beta = -0.0023$, $p < 1\%$) and Tobin's Q ($\beta = -0.0789$, $p < 1\%$), suggesting that the profitability decreases when the size of a company increases, especially in the long-term. Which is stresses the complex nature of operations and organizational structures of larger companies leading to inflexibility and a negative association. The effect of leverage is only significant in the short-term ($\beta = -0.1170$, $p < 1\%$), indicating that firms with higher debt relative to equity tend to have a lower ROA, in line with previous literature. This effect is not clear in the long-term, due to insignificance ($\beta = -0.0398$). R&D intensity has a strong negative association with ROA ($\beta = -0.2130$, $p < 1\%$), indicating that higher R&D may not result in a direct increase in profitability in the short-term, which is in line with theory that upfront investments that do not immediately translate into profitability. Conversely, as expected, the R&D intensity has strong positive association with Tobin's Q ($\beta = 1.4820$, $p < 1\%$), indicating a long-term positive effect of R&D on the profitability of a firm. The capital intensity is negative and significant in both the short-term ($\beta = -0.0087$, $p < 1\%$) and long-term ($\beta = -0.0788$, $p < 1\%$). This aligns with the literature, suggesting that a company which uses old machinery requires more assets to produce the same one dollar of revenue output, therefore negatively impacting the financial performance. Growth has only a positive and significant impact ($\beta = 0.0612$, $p < 1\%$) on the short-term financial performance of a company and is not significant in the long-term ($\beta = -0.00716$), suggesting a long-term diminished contribution of growth, facing tougher competition, complex management and operations, and market saturation.

Model H1 presents a positive and statistically significant effect of carbon disclosure on short-term financial performance (ROA), with a coefficient of 0.0089 at a 1% significant level, which supports hypothesis 1. The coefficient implies that for each one-unit increase in carbon disclosure score, e.g. moving from lowest to highest rating, the ROA would be expected to increase by 0.89%, holding all else constant. This is a modest relative effect, but the economic significance depends on the scale of the business. For large firms with substantial assets, even a small percentage change could represent a significant monetary impact. The findings align with the theoretical expectation that transparent reporting on carbon emissions can be a strategic tool that adds value to a firm, enhancing its reputation, reducing immediate information asymmetry, and increasing stakeholder trust.

Model H2 presents a positive and statistically significant effect of carbon disclosure on long-term financial performance (Tobin's Q), with a coefficient of 0.0624 at 5% significant level, which supports hypothesis 2. The coefficient suggests that a one-unit increase in the carbon disclosure score would result in an increase of approximately 6.24% of Tobin's Q. Considering that the natural logarithm was taken from Tobin's Q, which is a ratio of market value to book value of assets, even a small increase could be economically meaningful. If a firm's Tobin's Q is 1, indicating an equal market to book value of assets, an increase of 0.0624 in the natural logarithm of Tobin's Q corresponds to the market valuing the firm's assets at approximately 6.43% more than the book value. This could represent a significant increase in long-term financial performance, which is stronger than the short-term effect. The results are in line with the literature and theory, which suggests that over time, high-quality carbon disclosure can lead to increase investor trust and customer loyalty, thereby contributing to a firm's financial performance in the long-term. In the short-term, the increase in financial performance provides an early indicator that firms engaging in carbon disclosure are starting to experience financial benefits, which lays the foundation for a long-term environmental strategy. It therefore not only serves immediate stakeholder expectations, but also establishes sustainable competitive advantages and long-term financial performance.

Model H3a presents a positive and statistically marginal significant effect of carbon performance on short-term financial performance (ROA), with a coefficient of 0.0008 at 10% significant level. The p-value indicates a marginal significant effect above the 5% significant level but below the 10% level, therefore the results should be interpreted with caution. The coefficient presents the marginal effect of a carbon performance improvement on the financial performance of a company. If a company, for example, invests significantly in energy-efficient technologies or shifts towards more sustainable materials, and this would result in an improvement of the carbon performance by one unit, this is associated with an increasement of 0.08% of a company's ROA. Nevertheless, the findings state that improvements of carbon performance can lead to immediate economic benefits through cost reductions and capitalization of "low-hanging fruits" in terms of carbon performance improvements, which are less capital-intensive and can provide increased financial performance.

Model H3b presents a positive and statistically significant effect of carbon performance on short-term financial performance (ROA), and a negative and statistically significant effect of the quadratic term of carbon performance on short-term financial performance. With a coefficient of 0.0044 and -0.0004, respectively, both at a 1% significance level. These findings support the hypothesis that a non-linear relationship model offers a superior fit to a linear model, however it does not support hypothesis 3 of a U-shaped relationship. Contrarily, the relationship exhibits an inverse U-shaped relationship, in line with the findings of Misani and Pogutz (2015) and Brammer and Millington (2008). As the carbon performance of a firm continues to increase, the positive trend will reach a turning point where the economic costs outweigh the additional benefit and even illustrates a negative relationship after a certain turning point. This results in a negative effect on financial performance in the short-term after a certain threshold, which is at a carbon performance of 5.5 and carbon intensity of 0.0041 in the natural log scale of carbon performance based on the coefficients found in this study, all else constant. A company with a revenue of €1 million, a carbon intensity of approximately 0.0041 at the turning point would correspond to a total GHG emissions of about 4,087 tonnes. Meaning, that at the threshold where additional carbon performance improvements begin to negatively impact the financial performance, the company would be emitting around 4,087 tonnes GHG for every €1 million revenue, which is the equivalent to the emissions of approximately 210 homes for one year (Milieu Centraal, 2023).

Model H4a presents a positive and statistically significant effect of carbon performance on long-term financial performance (Tobin's Q), with a coefficient of 0.0560 at 1% significant level. An increase of carbon performance of 1, results in an increase of 5.6% of Tobin's Q, holding al else equal. The findings are in line with the NRBV, which implies that firms that are capable of shifting their strategies towards long-term environmental sustainability, as proven by their carbon performance, are able to leverage these capabilities to gain a competitive advantage and hereby increase their financial performance. The positive coefficient is in line with the theoretical argument of competitive advantage and instrumental stakeholder theory, that carbon performance could act as a sustainable cost-based competitive advantage and product differentiator.

Model H4b presents a positive and statistically significant effect of carbon performance on long-term financial performance (Tobin's Q), and a positive and statistically significant effect of the quadratic term of carbon performance on long-term financial performance. With a coefficient of 0.0433 and 0.0014, respectively, both at a 1% significance level. These findings support the hypothesis that a non-linear relationship model offers a superior fit to a linear model, therefore supports hypothesis 4 of an inverted U-shaped relationship. The positive quadratic term of carbon performance suggests that as carbon performance improves beyond a certain point, the financial performance continues to benefit. Although at a smaller rate, which suggests a diminishing of marginal return and a curvilinear relationship, where the marginal increase of financial performance starts to decrease after a certain threshold. An initial investment in carbon performance can lead to significant cost savings and revenue opportunities, however, as the carbon performance improves, the cost of achieving additional reductions often increase, while the benefits of this improvements decrease. Besides, the market's response to further carbon performance improvements become saturated, as these improvements become more widespread with the competition, implementing comparable sustainability initiatives. This might implicate an optimal level of carbon performance where the financial performance is maximized.

Furthermore, the findings present an incentive for carbon greenwashing. The regression results reveal that the coefficient for carbon disclosure on short-term financial performance is 0.0089, which is stronger and notably more significant than that of carbon performance in the short-term being 0.0008. Similarly, for long-term financial performance, carbon disclosure has a coefficient of 0.0624, while carbon performance has a lower coefficient of 0.0560. These figures suggest that the market reacts more favourable to disclosure about carbon emissions than to actual reduction of emissions. This could incentivize firms to concentrate on disclosure rather than substantive actions. If the relationship is stronger for carbon disclosure, then firms might want to report comprehensively on their carbon actions without necessarily engaging in proportionate carbon reduction strategies. This could serve as a starting point for carbon greenwashing, where companies could leverage disclosure as a means to project a sustainable image while their actual environmental impact remains moderate. In other words, this would promote a reporting-oriented approach rather than a reduction-oriented approach.

Table 4: Model regression results in the short-term

Results of the random effect multiple regression model in the short-term, represented by ROA.

ROA	Model a	Model H1	Model H3a	Model H3b
CD		0.0089***		
		(0.003)		
CP			0.0008*	0.0044***
			(0.000)	(0.001)
CP^2				-0.0004***
				(0.000)
Size	-0.0023***	-0.0028***	-0.0027***	-0.0024***
	(0.000)	(0.000)	(0.001)	(0.001)
Leverage	-0.1170***	-0.1170***	-0.1160***	-0.1160***
	(0.006)	(0.006)	(0.006)	(0.006)
R&D intensity	-0.2130***	-0.2150***	-0.2190***	-0.2184***
	(0.017)	(0.018)	(0.008)	(0.018)
Capital intensity	-0.0087***	-0.0087***	-0.0085***	-0.0084***
	(0.001)	(0.001)	(0.001)	(0.001)
Growth	0.0612***	0.0611***	0.0610***	0.0605***
	(0.003)	(0.003)	(0.003)	(0.003)
Region dummy	0.0042***	0.0048***	0.0039***	0.0038***
	(0.001)	(0.001)	(0.001)	(0.001)
Industry dummy	0.0004	0.0004	0.0004	-0.0001
	(0.001)	(0.001)	(0.001)	(0.008)
Constant	0.1380***	0.1390***	0.1420***	0.1320***
	(0.008)	(0.008)	(0.008)	(0.009)
Observations		12,687	12,687	12,687
R^2 overall		0.1431	0.1386	0.1423
R^2 between		0.1977	0.1929	0.1945
R^2 within		0.2041	0.2050	0.2055

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

Table 5: Model regression results in long-term

Results of the random effect multiple regression model in the long-term, represented by Tobin's Q.

Ln Tobin's Q	**Model b**	**Model H2**	**Model H4a**	**Model H4b**
CD		0.0624**		
		(0.028)		
CP			0.0560***	0.0433***
			(0.006)	(0.011)
CP^2				0.0014***
				(0.000)
Size	-0.0789***	-0.0836***	-0.1050***	-0.1060***
	(0.007)	(0.007)	(0.007)	(0.007)
Leverage	-0.0398	-0.0409	0.014	0.0154
	(0.066)	(0.067)	(0.065)	(0.065)
RD	1.4820***	1.4670***	1.3420***	1.3450***
	(0.234)	(0.234)	(0.233)	(0.232)
Capital intensity	-0.0788***	-0.0784***	-0.0650***	-0.0653***
	(0.008)	(0.008)	(0.008)	(0.008)
Growth	-0.0072	-0.0072	-0.0210	-0.0201
	(0.019)	(0.019)	(0.019)	(0.019)
Region dummy	0.0767***	0.0826***	0.0570***	0.0574***
	(0.018)	(0.018)	(0.010)	(0.017)
Industry dummy	0.0635***	0.0635***	0.0363***	0.0363***
	(0.011)	(0.011)	(0.011)	(0.011)
Constant	-0.0789***	1.3430***	1.6320***	1.6660***
	(0.007)	(0.114)	(0.116)	(0.121)
Observations		12,687	12,687	12,687
R^2 overall		0.2162	0.2443	0.2426
R^2 between		0.2303	0.2674	0.2662
R^2 within		0.0161	0.0202	0.0207

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

6 Robustness check

In this section, additional robustness checks are performed to account for possible endogeneity and to assess further potential sensitivity of the findings in this study.

6.1 Endogeneity

A fundamental problem in empirical studies is the presence of endogeneity, which arises when there's correlation between the independent variables and the error term (Antonakis et al., 2014). Two commonly known factors explain endogeneity in empirical studies. Firstly, simultaneous causality, which occurs when the independent and dependent variable both influence each other simultaneously. Secondly, omitted variable biases, which arise due to the impact of confounding factor, when a variable is excluded that correlates with both the dependent and independent variable. Endogeneity results in skewed and unreliable parameter estimates, which significantly reduces the reliability of the model (Roberts & Whited, 2013).

Simultaneous causality could exist between carbon disclosure and financial performance, and carbon performance and financial performance, that is, whether x drives y or other way around (Heckman, 2008). The slack resource theory of Waddock and Graves (1997) explains that financial performance may not only result from corporate efforts to address climate change but could also acts a driver behind such actions, implying potential simultaneity issues. Therefore, to address this problem, a lagged dependent variable with respect to the explanatory variables is used in a generalized method of moments (GMM) model, which is generally used for panel datasets, shown in Table 6. The lagged variables in the GMM model serve as instruments to address three sources of endogeneity, being, unobserved heterogeneity, dynamic endogeneity, and most important in this study, simultaneity (Ullah et al, 2018). Besides, the model is robust to the presence of autocorrelation which revealed in the preliminary assessments. The GMM model addresses endogeneity through an "internal transformation" of the data, which is a statistical method described by Roodman (2009) and Wooldridge (2010) that involves subtracting a variable's past value from its current value, thereby reducing the number of observations, and improving the model's efficiency. The Hansen J-statistic is not significant at the 5% level, suggesting that the instruments used are appropriate. The results are qualitatively in line with the previous main results of this study, showing the same direction of coefficients and, in most models, same size and significance level.

Table 6: GMM model

Results of the GMM model, which excludes model H3a and H4a, based on the conclusion that the exponential models fit better than the linear models. Model L.H3 and L.H4 represent model H3b and H4b, respectively.

	Dep: ROA	*Dep: Ln Tobin's Q*	*Dep: ROA*	*Dep: Ln Tobin's Q*
	Model L.H1	**Model L.H2**	**Model L.H3**	**Model L.H4**
ROA (L.1)	0.3100***		0.3070***	
	(0.026)		(0.020)	
Ln Tobin's Q (L.1)		0.6670***		0.6600***
		(0.022)		(0.034)
CD	0.0136***	0.0044*		
	(0.003)	(0.009)		
CP			0.0028***	0.0251***
			(0.001)	(0.007)
CP_2			-0.0003***	0.0008**
			(0.000)	(0.001)
Size	-0.0023***	-0.0318***	-0.0013***	-0.0409***
	(0.000)	(0.003)	(0.000)	(0.004)
Leverage	-0.0592***	-0.0542*	-0.0621***	0.0015
	(0.005)	(0.032)	(0.006)	(0.033)
RD	-0.0566***	1.1710***	-0.0531***	1.0680***
	(0.0158)	(0.124)	(0.017)	(0.120)
Capital intensity	-0.0058**	-0.0419***	-0.0061***	-0.0349***
	(0.001)	(0.005)	(0.001)	(0.005)
Growth	0.0728***	0.0006	0.0727***	0.0019
	(0.003)	(0.022)	(0.003)	(0.022)
Region dummy	0.0025***	0.0214***	0.0019**	0.0140**
	(0.001)	(0.006)	(0.001)	(0.006)
Industry dummy	0.0001	0.0206***	0.0002	0.0130***
	(0.001)	(0.004)	(0.001)	(0.004)
Constant	0.0882***	0.5310***	0.0788***	0.6320***
	(0.006)	(0.047)	(0.007)	(0.058)
Observations	10,023	10,023	10,023	10,023
Hansen J-test (P-value)	(0.1301)	(0.032)	(0.1618)	(0.104)

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

Omitted variable bias occurs when financial performance and carbon performance or carbon disclosure are driven by one or multiple factors that are unobservable or not measurable. The explanatory variable could be correlated with the error term if one or multiple relevant explanatory variables are omitted from the sample, therefore the modelled estimates do not yield the true parameter's value (Wilms, 2021). This endogeneity issue is address, in line with Siddique et al. (2021), Alsaifi et al. (2020) and He et al. (2013), by employing an instrumental variable two-stage least squares (IV-2SLS) model. The model requires the use of instrumental variables that are simultaneously relevant and exogenous, therefore the instrument should be correlated with the independent variable but not with the dependent variable. The first stage generates unbiased predicted values by regressing each independent variable on all exogenous variables and additional instrumental variables. The second stage regresses the main dependent variable on the predicted values from the first stage and any exogenous variables to obtain consistent parameter estimates by addressing potential biases from endogeneity. The first instrumental variable, in line with the reasoning of Larcker and Rusticus (2010) and Brouwers et al. (2017), is the industry-year average carbon disclosure and carbon performance. The choice is supported by the rationale that the industry averages are likely correlated with the carbon practices of an individual firm due to industry norms and industry peer pressure, however are unlikely to have a direct effect on a firm's financial performance, which is more prone to firm-specific factors. The other instrumental variable is country-year average carbon disclosure and carbon performance, which is consistent with previous studies (Alsaifi, 2020; Jo & Harjoto, 2012; Surroca et al., 2010; Schreck, 2011) and considered important to examen in environmentally focused studies. The average level of carbon disclosure and carbon performance per country for a given year is likely determined by external factors such as disclosure regulations and cultural norms that are not correlated with the financial performance of a single company (Dhaliwal, 2011). Countries with strict carbon regulating and high levels of environmental awareness urge individual firms to increase their carbon performance and to disclose carbon information to meet broader societal demand for sustainability (Albuquerque, 2019).

Before performing the IV-2SLS model, some additional tests are performed to test the relevance, identification, and validity of the instrumental variables, their results are stated in Table 7. First, the Kleibergen-Paap rk Lagrange Multiplier (LM) test is employed to test the under identification of the variable, meaning that the excluded instruments are "relevant", therefore correlated with the endogenous regressors. The test for every model rejects the null hypothesis of under identification, which suggests that the instrumental variables are indeed relevant. This provides statistical evidence to suggest that they are correlated with the endogenous explanatory variables in the model (Windmeijer, 2018). Secondly, after establishing the correlation with the Kleibergen-Paap rk LM test, the Stock-Yogo weak identification test is performed to test if the excluded instruments are weakly correlated with the endogenous regressors (Stock and Yogo, 2005). Estimators may perform poorly if the instruments are weak. The instrumental variables are considered weak when their test statistics do not exceed the critical threshold value. The Kleibergen-Paap rk Wald F statistic is favoured over the Cragg-Donald Wald F statistic due to its robustness to heteroskedasticity and autocorrelation, which is identified in this panel dataset based on the preliminary assessments. All statistics are above the critical threshold value of the 25% maximal IV of 7.25. The statistics suggest strong instruments and no biased estimates due to weak instrument problems. Lastly, the Hansen J statistic test is performed to test the validity of the instrumental variables in the form of overidentification of restrictions. The test is consistent in the presence of heteroskedasticity and autocorrelation, which, as mentioned before is present in this study. The null hypothesis states that the instruments are uncorrelated with the error term and that they are valid. The P-values exceed the significance level of 10%, therefore the null hypotheses cannot be rejected for all models.

The results of the first stage of the IV-2SLS model are presented in Table A.6 show statistically robust results that are in line with theory on the relationship between the instrumental variables and the dependent variables. The significant and consistent coefficients for both the instrumental variables of carbon disclosure and carbon performance validate their use as instruments in the second stage.

The results of the second stage of the IV-2SLS model are presented in Table 7 and are statistically in line with the previous results, therefore after controlling for endogeneity, the relationship persist. Furthermore, all models present higher coefficients, which can be substantiated by the power of the instrumental variables. The variation in the explanatory variable that is uncorrelated with the error term is better isolated, which increases the precision of the estimates by mitigating biases associated with endogeneity (Ullah et al., 2021)

All alternative models, including IV-2SLS and the GMM, converge on the same conclusion, namely, that carbon disclosure positively affects financial performance in the short and long-term, and carbon performance follows an inverted U-shaped relationship in the short-term and diminishing marginal returns in the long-term.

Table 7: Second stage of the IV-2SLS model

Results of the second stage of the IV-2SLS model, which excludes model H3a and H4a, based on the conclusion that the exponential models fit better than the linear models. Model H3 and H4 represent model H3b and H4b, respectively. The second stage uses these predicted values of the first stage to obtain consistent and unbiased estimates of the parameters in the regression model.

	Dep: ROA	*Dep: Ln Tobin's Q*	*Dep: ROA*	*Dep: Ln Tobin's Q*
	Model H1	**Model H2**	**Model H3**	**Model H4**
CD	0.0619***	1.1460***		
	(0.012)	(0.156)		
CP			0.0334***	0.2890***
			(0.005)	(0.057)
CP_2			-0.0030***	0.0317***
			(0.000)	(0.005)
Size	-0.001	-0.0356***	-0.0024***	-0.1090***
	(0.001)	(0.007)	(0.000)	(0.004)
Leverage	-0.0655***	-0.2350***	-0.0760***	-0.1340**
	(0.005)	(0.060)	(0.006)	(0.062)
RD	-0.0697***	3.2400***	-0.0223	3.1870***
	(0.016)	(0.148)	(0.019)	(0.168)
Capital intensity	-0.0097***	-0.0960***	-0.0120***	-0.0893***
	(0.001)	(0.008)	(0.001)	(0.009)
Growth	0.0701***	0.3350***	0.0745***	0.3810***
	(0.004)	(0.038)	(0.004)	(0.039)
Region dummy	0.0006	-0.0130	0.0078***	0.0648***
	(0.001)	(0.013)	(0.001)	(0.013)
Industry dummy	-0.0001	0.0461***	0.0030***	0.0532***
	(0.001)	(0.007)	(0.001)	(0.008)
Constant	0.1380***	1.5080***	0.1770***	2.2480***
	(0.006)	(0.070)	(0.011)	(0.123)
Kleibergen-Paap rk	148.125	153.200	205.140	207.120
LM Statistic (P-value)	(0.000)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap rk	132.785	234.960	105.829	265.700
Wald F statistic				
Hansen J statistics	1.068	2.560	1.040	1.480
(P-value)	(0.300)	(0.108)	(0.307)	(0.231)

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

6.2 Carbon and non-carbon-intensive industries

Industries vary widely in their levels of carbon emissions due to the differences in their production processes, resource requirements, and regulatory scrutiny. This sensitivity analyses separates carbon intense industries from non-carbon intense industries based on assumptions. By making this distinction potential insights about the relationship between different industry types, and carbon performance and disclosure could reveal. Carbon-intensive industries, such as manufacturing, energy production, and transport, are inherently associated with a larger carbon footprint due to the nature of their operations. They may be influenced more by investors and regulators, which could influence how carbon disclosure practices impact financial performance. Additionally, cost-saving measures through emissions reduction practices could have a more significant impact in carbon-intense industries. The study employs a binary dummy variable approach to further investigate how these differences in carbon intensity affect financial outcomes.

The binary dummy variable is created where 1 represents a carbon-intensive industry and 0 represents a non-carbon-intensive industry. Heavy manufacturing (SIC 2000-3499), Transportation and Utilities (SIC 4000-4999) and Mining (SIC 1000-1499), are classified as carbon-intensive industries, due to their reliance on fossil fuels and energy-intensive processes, especially industries such as steel and cement production within the heavy manufacturing sector and the mining sector are among the largest industrial contributors to GHG emissions (Smith, 2008). The remaining sectors, Agriculture, Forestry and Fishing (SIC 0100-0999), Construction (SIC 1500-1799), Consumer Goods Manufacturing (SIC 3500-3499), Wholesale and retail trade (SIC 5000-5999), Real estate, Finance and Services (SIC 6500-8999), are classified as non-carbon-intensive. Following this distinction, 52.35% is classified as non-carbon-intensive and 47.65% as carbon-intensive, creating an even distribution between the two industry types. The results of the analyses are presented in Table 8, and several insights emerge.

In the short-term (Model H1), non-intensive industries exhibit a relatively small but significant positive relationship between carbon disclosure and financial performance, indicating that even in non-intensive-carbon industries, transparency contributes positively to financial returns. Moreover, in carbon-intensive industries, the relationship is stronger, as shown by larger coefficient, suggesting that stakeholders may attribute a premium in the short-term to disclosure in industries where the impact is more significant.

In the long-term (Model H2), the relationship of carbon disclosure and financial performance between intensive and non-intensive industries changes. For non-intensive industries, the coefficient for carbon disclosure increases significantly to 0.100, while staying significant. This larger coefficient suggests that the positive effect of carbon disclosure on financial performance is consistent over time. In the long-term, the coefficient for carbon disclosure of carbon-intensive industries is 0.0201, which, although positive, is lower than in the non-intensive industries. Since, industry scrutiny could impact the coefficient, as non-intensive industries might not experience the same level of scrutiny for carbon disclosure practices. Therefore, when non-intensive industries engage in carbon disclosure, it might signal expectational commitment to sustainability, potentially leading to greater differentiation and a positive response from stakeholders.

In the short-term (Model 3) and in the long-term (Model H4) only the intensive industries present a significant relationship between carbon performance and financial performance in line with previous literature (Gonenc & Scholtens, 2017; Jo & Na, 2012; Trinks et al, 2022). Which indicate higher sensitivity in carbon-intensive industries of financial performance to carbon performance improvements compared to non-intensive industries. Efforts to improve carbon performance are likely to be both more challenging and potentially more rewarding due to a higher starting level of emissions in carbon-intensive industries. There is a clear signal to these companies that carbon performance matters to their bottom line. In contrast, for non-intensive industries, the lack of significance suggests that the financial returns on carbon performance improvements may not be as immediate or direct. This could be explained by their lower levels of emissions, therefore improvements in carbon performance might not be visible or impactful to stakeholders or operations, because these industries have other more significant drivers of financial performance that overshadow the effect of carbon performance improvements.

Concluding, companies in carbon-intensive industries have a more pronounced incentive to invest in carbon performance improvements and reporting practices, as these efforts are directly correlated with financial performance improvements. Furthermore, disclosure yields immediate positive financial returns for companies in these industries, driven by high environmental risks and stakeholder expectations for effective risk management. However, the long-term financial benefits in these industries tend to diminish as disclosure practices become normalized. In contrast, non-intensive industries initially see modest financial benefits from disclosure, but over time, the significance of these practices grows, indicating a rising appreciation from stakeholders.

Table 8: Carbon-intensive industry analyses

Results of carbon-intensive and non-intensive industry distributed regression. Model H1 and H3 represent the short-term effect and H2 and H4 the long-term.

	Non-Intensive	*Intensive*	*Non-Intensive*	*Intensive*	*Non-Intensive*	*Intensive*	*Non-Intensive*	*Intensive*
	Model H1	**Model H1**	**Model H2**	**Model H2**	**Model H3**	**Model H3**	**Model H4**	**Model H4**
CD	0.0083**	0.0098**	0.1000**	0.0201*				
	(0.003)	(0.004)	(0.041)	(0.028)				
CP					0.0045	0.0051***	0.0277	0.0588***
					(0.003)	(0.001)	(0.025)	(0.012)
CP^2					-0.0004	-0.0004***	0.0026	0.0006***
					(0.000)	(0.000)	(0.003)	(0.000)
Size	-0.0023***	-0.0036***	-0.0766***	-0.0926***	-0.0018**	-0.0037***	-0.0968***	-0.1200***
	(0.001)	(0.001)	(0.010)	(0.010)	(0.001)	(0.001)	(0.011)	(0.010)
Leverage	-0.1090***	-0.1290***	-0.0632	-0.0162	-0.1080***	-0.1260***	-0.0189	0.0471
	(0.010)	(0.008)	(0.102)	(0.077)	(0.009)	(0.008)	(0.099)	(0.076)
RD	-0.2210***	-0.1940***	1.4560***	1.5140***	-0.2220***	-0.2050***	1.4440***	1.3160***
	(0.024)	(0.028)	(0.250)	(0.477)	(0.025)	(0.029)	(0.249)	(0.464)
Capital intensity	-0.0093***	-0.0083***	-0.0806***	-0.0790***	-0.0092***	-0.0078***	-0.0686***	-0.0648***
	(0.001)	(0.001)	(0.013)	(0.010)	(0.001)	(0.001)	(0.013)	(0.0102)
Growth	0.0590***	0.0630***	0.0762**	-0.0777***	0.0587***	0.0620***	0.0656**	-0.0974***
	(0.004)	(0.004)	(0.030)	(0.022)	(0.004)	(0.004)	(0.030)	(0.022)
Region dummy	0.0039**	0.0060***	0.0519*	0.1190***	0.0034*	0.0042**	0.0263	0.0944***
	(0.002)	(0.002)	(0.029)	(0.022)	(0.002)	(0.002)	(0.027)	(0.020)
Constant	0.1250***	0.1380***	1.0270***	1.7140***	0.1130***	0.1380***	1.3130***	1.9990***
	(0.011)	(0.011)	(0.163)	(0.155)	(0.014)	(0.012)	(0.183)	(0.157)

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

6.3 Below and above threshold carbon performance

The regression results of carbon performance on financial performance exhibit a threshold value of 5.5, therefore this sensitivity analyses serves to comprehensively understand the relationship of carbon performance on financial performance below and above a certain threshold in the short-term. This is particularly important as firms strive for an equilibrium between environmental initiatives and economic benefits. This distinction will substantiate the decision-making process for investments in carbon reduction strategies. This examination is not only academically interesting, in line with prior studies like Misani and Pogutz (2015), but also carries substantial practical implications. Firms can utilize these insights to optimize their carbon performance without having to weight these improvements against a loss of profitability, which is particularly relevant with the increasing regulatory pressures and market expectations for sustainable operations. The following regression is applied to investigate the threshold effect:

$$\begin{aligned} ROA_{i,t} = {} & B_o + B_1 CP_{i,t} + B_2\, Threshold_{i,t} + B_3 (CP_{i,t} * Treshold_{i,t}) + B_4\, Size_{i,t} \\ & + B_5\, Leverage_{i,t} + B_6 R\&D_{i,t} + B_7\, Capital\ intensity_{i,t} + B_8\, Growth_{i,t} \\ & + B_9\, Region_i + B_{10}\, Industry_{i,t} + a_i + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{16}$$

$CP_{i,t}$ captures the effect of carbon performance below the threshold level. $Threshold_{i,t}$ is a dummy variable that equals 1 if the carbon performance is equal to or above the threshold value, and 0 otherwise. $CP_{i,t} * Treshold_{i,t}$ presents an interaction effect that captures the differential effect of carbon performance above the threshold level.

The results are presented in Table 9 and show that there is indeed a threshold effect in the relationship between carbon performance and financial performance in the short-term. The threshold dummy variable exhibits a positive and significant coefficient at the 10% significance level, suggesting that crossing the threshold of 5.5 has a positive effect on the financial performance, in addition to the base effect of carbon performance. The interaction term however is negative and significant at the 1% level, which indicates that the effect of carbon performance on financial performance becomes less positive when carbon performance surpasses the threshold level. Specifically, after the threshold level, each additional unit increase of carbon performance results in a decrease of financial performance by 0.0482 units more than the decrease that would be predicted by carbon performance alone.

The diminishing effect beyond this threshold underscores the strategic importance for companies to conduct an analysis of their sustainability investments. Recognizing the threshold's implications can guide firms in optimizing their environmental strategies to not only achieve sustainability goals but also to enhance shareholder value, inform stakeholders and shaping future policy recommendations in the sphere of corporate environmental responsibility.

Table 9: Short-term threshold interaction effect

The regression analysis shows an interaction effect between financial performance and carbon performance at threshold value of 5.5, showing that the relationship of carbon performance on financial performance in the short-term changes after surpassing the threshold value.

ROA	Model short-term interaction
CP	0.0034***
	(0.001)
Threshold dummy	0.0199**
	(0.008)
CP * Threshold	-0.0048***
	(0.001)
Size	-0.0023***
	(0.001)
Leverage	-0.1160***
	(0.006)
RD	-0.2220***
	(0.018)
Capital intensity	-0.0083***
	(0.001)
Growth	0.0603***
	(0.003)
Region dummy	0.0035***
	(0.001)
Industry dummy	-0.0001
	(0.001)
Constant	0.1280***
	(0.009)
Observations	12,687
R^2 overall	0.1444
R^2 between	0.1972
R^2 within	0.2062

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

6.4 Low and high initial level of carbon disclosure

The initial level of carbon disclosure may have a different impact on the financial performance of firms, suggesting that the starting level from which firms increase their disclosure practices plays a critical role. The information asymmetry theory argues that firms with low initial carbon disclosure might have greater potential to benefit from increased disclosure due to the reduction of information asymmetry between the firms and its stakeholders (Adhikari & Zhou, 2021). Firms could enhance their reputation, reduce perceived risk, and potentially lower the cost of capital. The signaling theory suggests that increased carbon disclosure act as a positive signal to the market, particularly for firms with previously low levels of disclosure (Lu et al., 2021). A substantial improvement of carbon disclosure can signal a commitment of management to transparency and sustainability practices. Contrarily, for firms already at high levels of carbon disclosure, the marginal benefit of further disclosure may be less pronounced. However, firms with high levels of carbon disclosure may be perceived as market leaders in transparency and environmental responsibility. The differentiation on a high level can translate into a competitive advantage, as it may attract investors who are increasingly concerned about environment issues. Furthermore, an initial high level of disclosure can signal to investors that a firm is not only compliant with current regulations but also proactively engaged with potential future regulations. This increases investor confidence and potentially lead to a lower risk premium, as investors feel more secure about the firm's long-term strategy.

This sensitivity analyses examines firms with varying initial levels of carbon disclosure. Companies are categorized into low and high carbon disclosure groups based on their initial level of carbon disclosure compared to the median. The results are presented in Table 10.

In the short-term (Model H1), the coefficient for low initial level carbon disclosure companies is positive but not statistically significant, which suggests an unclear relationship based on the data. Contrarily, the coefficient of companies with a high initial level of carbon disclosure is positive and statistically significant at a 5% level, indicating that carbon disclosure is likely perceived positively by the market and could be contributing to financial performance.

In the long-term (Model H2), both low and high carbon disclosure companies experience a positive impact from carbon disclosure on financial performance, with an even larger effect for high carbon disclosure companies. This suggests that while carbon disclosure benefits all firms in the long-run, those with a high initial level of disclosure are better positioned to capitalize the improvement of carbon performance, potentially due to a long-term established competitive advantage.

The differences between the short-term and long-term effect for low carbon disclosure firms could be attributed to a lagged market response to improved disclosure practices. Initially, the financial benefits might not be immediate for low carbon disclosure companies, while as the company continues to build its disclosure practices, the positive effect is more noticeable. Contrarily, high carbon disclosure companies might be benefiting first-mover advantages in the short-term, as they are already perceived as leaders in transparency, which can reflect in their financial performance. In the long-term, these firms continue to benefit, possibly due to sustained investor confidence and customer engagement.

The findings suggest that carbon disclosure should be part of long-term strategic approach rather than a short-term tactic for improving financial performance. For companies with low initial carbon disclosure, the findings highlight the importance of persistence in carbon disclosure practices, as the benefits tend to pay-off in the long-term. For high initial carbon disclosure companies, the analysis underlines the importance of maintaining high disclosure standards, as the benefits are significant both short and long-term. The increased coefficients form short to long-term indicates that the market may reward enduring commitment to transparency and may reflect a growing trend of investor preference for companies with robust carbon disclosure practices.

Table 10: Initial carbon disclosure level analyses

Results of low and high initial carbon disclosure regression. Model H1 and H3 represent the short-term effect and H2 and H4 the long-term.

	Low CD	*High CD*	*Low*	*High*
	Model H1	**Model H1**	**Model H2**	**Model H2**
CD	0.0045	0.0209**	0.0743**	0.1400**
	(0.004)	(0.008)	(0.038)	(0.073)
Size	-0.0024***	-0.0036***	-0.0830***	-0.0804***
	(0.001)	(0.001)	(0.008)	(0.009)
Leverage	-0.1030***	-0.1200***	-0.1550**	-0.0206
	(0.0066)	(0.010)	(0.070)	(0.107)
RD	-0.2040***	-0.1520***	1.8590***	1.2400***
	(0.020)	(0.028)	(0.328)	(0.326)
Capital intensity	-0.0077***	-0.010***	-0.080***	-0.088***
	(0.001)	(0.001)	(0.010)	(0.013)
Growth	0.0596***	0.0640***	-0.0082	-0.0190
	(0.004)	(0.004)	(0.026)	(0.026)
Region dummy	0.0054***	0.0035**	0.0800***	0.0622**
	(0.002)	(0.002)	(0.020)	(0.026)
Industry dummy	-0.0005	0.0007	0.0604***	0.0689***
	(0.001)	(0.001)	(0.012)	(0.016)
Constant	0.1320***	0.1460***	1.3690***	1.2270***
	(0.009)	(0.012)	(0.122)	(0.174)
Observations	6,338	6,349	6,338	6,349
R-squared within	0.2126	0.1783	0.0165	0.0206
R-squared between	0.1554	0.2100	0.2295	0.2025
R-squared overall	0.1354	0.1745	0.2071	0.2161

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

7 Discussion & Conclusion

This paper explores the effect of carbon disclosure and carbon performance on financial performance in the short-term and the long-term examining a large final dataset of 12,687 firm-year observations from a uniquely long period from 2014 to 2023 in different global regions. The findings are based on a robust theoretical framework and an extensive empirical analysis. The findings show that carbon disclosure positively influences both short-term and long-term financial performance. Additionally, the paper reveals a nuanced relationship between carbon performance and financial performance, characterized by an inverted U-shaped curve in the short and long-term, and diminishing returns beyond a certain threshold, indicating the complexity of balancing environmental practices with financial operations. The paper contributes to the ongoing debate on the financial effectiveness of sustainable business operations, specifically carbon mitigation and reporting practices. This section highlights the theoretical implications of these findings, presents conclusive insights, and presents the limitations and potential undiscovered areas for further research.

7.1 Theoretical implications

The existing literature has predominantly found a positive effect of both carbon disclosure and carbon performance on financial performance. However, a mixed non-linear relationship of carbon performance on financial performance. This paper re-examines these relationships by offering a comprehensive analysis that challenges previous assumptions and broadens the existing literature on sustainable finance.

Carbon disclosure, suggested by the findings, serves as a competitive advantage and strategic tool that can enhance a firm's reputation and trust among stakeholders, aligning closely with the RBV and signaling theory (Barney, 2001; Alsaifi et al., 2020). The significant impact of carbon disclosure on short-term financial performance points out the immediate financial impact when firms engage in transparent carbon disclosure practices, which is a reflection of decreased information asymmetry and enhanced reputation among investors and customers. Moreover, the strong positive impact of carbon disclosure on long-term financial performance offers empirical support to the legitimacy theory, supported by existing research, suggesting that companies that meet the societal expectations on carbon transparency are rewarded with sustained financial performance. Besides, the findings that firms with a higher initial level of carbon disclosure experience more financial benefits in the short and long-term suggest a cumulative advantage and contribute to the positive feedback loop described by the signalling theory of Spence (1973). This adds to the literature by highlighting the importance of historical levels of disclosure in assessing the financial impacts of increased transparency.

Carbon performance in relation to financial performance presents more complex findings than found in prior research (Nishitani & Kobubu, 2012; Trinks et al, 2020). In the short-term, it contrasts with the assumption that immediate profitability follows from investments in carbon reducing practices. Instead, the findings imply a nuanced dynamic where initial investments in carbon performance might not always results in short-term profitability in line with Lewandowski (2017) and Trumpp and Guenther (2015). The observed inverted U-shaped relationship suggest that beyond a certain threshold, the cost of additional improvements of carbon performance may outweigh the financial benefits. In the long-term, the findings reveal an inverted U-shaped relationship as well. These findings challenge the simplistic notion of a linear, always positive relationship between environmental initiatives and financial improvements, which is often implied in earlier research (Kobubu, 2012; Trinks et al., 2020; Rokhmawati, 2015). The findings present a balance between the benefits of carbon performance, such as operational efficiencies, and differentiation of sustainable products, and the costs associated with implementing these environmental measures. These findings extend the debate on the optimal level of environmental performance within firms and contributes to the understanding of the strategic influence of carbon performance on financial performance.

Furthermore, by differentiating between carbon-intensive and non-carbon-intensive industries, the paper adds complexity to the understanding of how carbon disclosure and performance impact financial outcomes across different industries. The distinction helps to clarify why some industries may see more significant financial benefits from environmental efforts than others, contributing to a more nuanced industry-specific approach in future research. By examining both carbon disclosure and carbon performance, this research contributes to a more comprehensive empirical understanding.

Lastly, the distinctive approach of examining both carbon disclosure and carbon performance within a single study, represent a unique contribution to the field of financial economics and environmental sustainability, contradicting with previous studies (Clarkson et al., 2008; Matsumura et al., 2014). The paper hereby offers a more holistic view on environmental strategies of companies, highlighting both communication about and actual implementation of carbon reduction practices. This creates the possibility to highlight the potential incentive for carbon greenwashing. A gap reveals between the valuation of reported intentions and tangible environmental outcomes due to a more favourably market reaction to disclosure practices than actual emission reductions. The gap could encourage firms to focus on enhancing the visibility of their carbon reporting without equally investing in the substantive actions to reduce. The findings critically enrich the discussion around the effectiveness of corporate sustainability practices.

7.2 Conclusion

The urgency of addressing climate change has directed corporate focus towards sustainable operations, particularly in carbon management. This paper empirically examens how carbon disclosure and performance affect the financial performance in the short and long-term. The findings present a nuanced landscape where carbon disclosure and carbon performance indeed play a critical role in shaping the financial performance of a company. The central question in this paper was therefore:

What is the impact of carbon disclosure and carbon performance on financial performance of the world's largest companies in the short and long-term?

Consistent with hypotheses, carbon disclosure was positively associated with both short-term and long-term financial performance, stressing the value of transparency, and building investor trust over time. On the other hand, carbon performance demonstrated a complex influence, with a non-linear model offering a better fit than a linear model in both the short and long-term. However, in the short-term, an inverse U-shaped relationship is found, contrary to the expected U-shaped relationship, implying that beyond a certain threshold, additional carbon performance improvements could negatively affect short-term financial performance. In the long-term, an initial positive effect is found, which aligns with the NRBV theory that strategic long-term environmental sustainability practices can lead to a competitive advantage. However, after a certain point, diminishing marginal returns are present.

Further robustness was conducted to test the sensitivity of the analyses and to address possible endogeneity issues. The study employs a GMM model and an IV-2SLS model to deal with endogeneity. The GMM model, which accounts for unobserved heterogeneity, dynamic endogeneity, and simultaneity, and the IV-2SLS model, which addresses omitted variable bias, both reinforce the main findings, indicating the robustness of the results. The analysis further differentiates between carbon-intensive industries and non-carbon-intensive industries, indicating is a clear signal to companies in carbon-intensive industries that carbon performance matters to their bottom line in both the short and long-term. The findings further suggest that carbon disclosure significantly increase financial performance in carbon-intensive industries in the short-term. However, as these practices become normalized, the long-term financial improvements in these industries tend to diminish. In contrast, non-carbon-intensive industries reveal the opposite relationship, with an only modest financial improvements in the short-term but over time, the impact of the disclosure practices grows, reflecting an increasing appreciation from stakeholders. The findings underscore the need for carbon-intensive industries to capitalize on the initial short-term financial benefits, while non-carbon-intensive industries should invest in sustainable, long-term disclosure strategies to benefit from the gradually increasing financial returns driven by rising stakeholder appreciation. Moreover, the paper investigates the effect of carbon performance below and above a certain threshold. Carbon performance improvements have a positive impact on financial performance up to a certain point, beyond which the benefits diminish or even become negative. This threshold analyses emphasizes the strategic importance of balancing environmental initiatives with economic benefits, suggesting firms need to optimize their sustainability investments carefully. Lastly, the paper explores how the initial level of carbon disclosure influences its impact on financial performance. The results suggest that firms with a high initial level of carbon disclosure see a more substantial positive effect on both short and long-term financial performance compared to firms with lower initial disclosure levels. This indicates that starting from a higher baseline in carbon disclosure practices can enhance a firm's ability to capitalize on environmental transparency for financial gain.

The findings offer significant practical insights for managers, policy-makers, and investors. The paper underscores the strategic value of carbon disclosure in enhancing corporate reputation and market valuation, aiming for a proactive approach to sustainability reporting as a competitive advantage. Highlighting the importance of strategic investments in carbon performance improvements, emphasizing the identification of cost-effective initiatives and the careful evaluation of their long-term financial impacts, given the diminishing returns beyond a certain efficiency threshold. Suggesting a need for companies to balance the short-term costs associated with sustainability initiatives against potential long-term value creation, necessitating a shift towards prioritizing sustainability in corporate strategies.

For policymakers, the paper advocates for regulatory frameworks that incentivize comprehensive carbon disclosure and effective carbon reduction strategies, adjusted to the unique characteristics of different industries. It also suggests the development of industry-specific guidelines and benchmarks to encourage transparency and sustainability leadership.

For investors, the paper reinforces the importance of incorporating carbon management metrics into investment criteria, highlighting the potential of carbon-focused investments to deliver competitive returns while contributing to sustainability goals. Moreover, investors are advised to refine risk assessment and valuation models to account for the nuanced effects of carbon management practices, including the strategic value of carbon disclosure in assessing long-term viability and growth prospects.

Concluding, the paper advocates for the strategic integration of carbon management practices within corporate operations, highlighting the duplicity of embracing environmental leadership towards sustainable development and leveraging these practices for financial growth. Fostering a future where sustainable practices are not just ethical imperatives but crucial drivers of economic prosperity.

7.3 Limitations & Further research

Several limitations should be considered when interpreting the findings of this paper, which in turn opens opportunity for further research. A first limitation is the sample of this study, which consists of the largest listed global companies by capitalization. Although representing a uniquely longitudinal sample period, which rejects the time and size bias argument. The paper's findings cannot be generalized to small or medium size firms. This field of comparison could provide more insights into the relationship of environmental strategies and financial performance. Secondly, a proxy for carbon disclosure is used which represents a company's transparency and engagement, although not dependent on voluntary carbon disclosure or a single source, using CDP data, which is extensively utilized, would offer more accuracy and depth given its comprehensive collection of self-reported information. Besides reflecting a level of carbon engagement, it would offer a more profound representation of different levels of carbon disclosure. Furthermore, carbon performance is based on a company's GHG emissions, which cannot completely be eliminated, indicating the need for another proxy to accurately reflect carbon performance. Besides, the GHG emission data is based on a four-step approach from Eikon, which also includes an estimation model, while filling unavailable gaps and increasing the overall dataset, this could strongly decrease the precision and accuracy of the data. Therefore, relying on actual company emission reports would offer greater accuracy and transparency. Moreover, the fundamental business metric used for measuring carbon intensity might have a relationship with the selected indicators of financial performance. Future research will need to explore the impact of variations in the business metric underlying relative emission measurements.

Some different empirical studies could be examined as well. First, other types of environmental performance indicators, such as pollution, could offer a broader perspective on the topic, which enables a deeper understanding of the complex relationship between various environmental strategies and financial outcomes. Secondly, the study consists of a single polynomial regression analysis, whereas further empirical studies may implicate other non-linear models. Finally, specific regulatory implications could be measured by isolating the effect of a single carbon regulation on financial companies. This is especially relevant due to the significant varying internalization of carbon emissions costs across different historical and institutional settings.

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9 Appendix

Figure A.1: Scatter plots of residuals

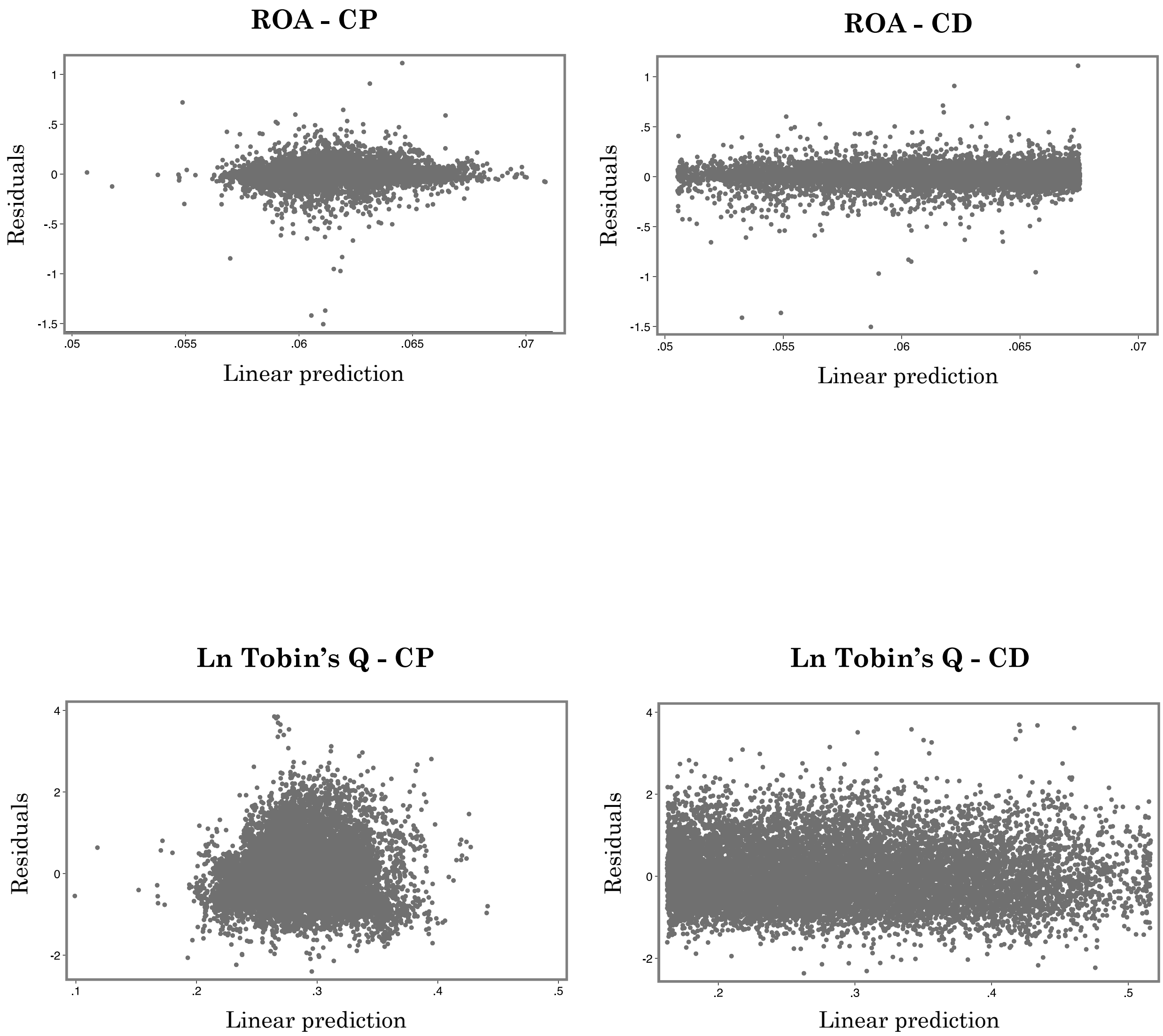


Table A.1: Winsorization table

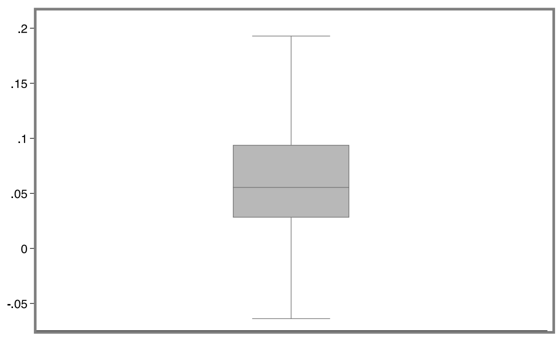
Description of summary statistics for all variables both before and after winsorization, which limits extreme values to reduce the influence of outliers.

	Mean	**Median**	**SD**	**Min**	**Max**	**N**
ROA	.062	.055	0.086	-1.445	1.178	12,687
ROA – 92%	.063	.055	0.060	-.064	.201	12,687
Ln Tobin's Q	.285	.178	0.742	-2.104	4.114	12,687
Ln Tobin's Q – 98%	.284	.178	0.725	-1.073	2.307	12,687
CP	4.959	4.53	2.762	-9.654	17.22	12,687
CP – 90%	4.958	4.53	2.730	-1.176	12.54	12,687
CP^2	32.22	20.54	31.917	0	296.537	12,687
CP^2 – 90%	30.737	20.54	27.357	.042	93.552	12,687
Size	17.649	17.371	2.802	9.579	27.086	12,687
Size – 98%	17.648	17.371	2.768	12.137	24.25	12,687
Leverage	.242	.23	0.169	0	2	12,687
Leverage – 98%	.24	.23	0.162	0	.699	12,687
RD	.064	.021	0.822	-.787	85.619	12,687
RD – 98%	.046	.021	0.070	0	.406	12,687
Capital intensity	3.027	1.362	106.795	.155	11910	12,687
Capital intensity – 98%	1.704	1.362	1.198	.442	7.954	12,687
Growth	.921	.062	87.342	-.95	9,833.857	12,687
Growth – 96%	.092	.062	0.193	-.294	.75	12,687

90% Winsorization describes the process where the bottom 5% and the top 5% of data points are replaced with the closest remaining values in the data set, effectively reducing the influence of outliers. For 98% Winsorization, only the bottom 1% and the top 1% are replaced. These percentages indicate the portion of the data that remains unchanged, while the remainder is adjusted to decrease the impact of extreme values.

Figure A.2: Box plot dependent variables

ROA



LnTobin's Q

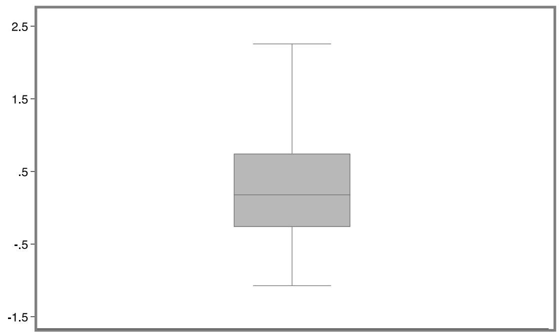
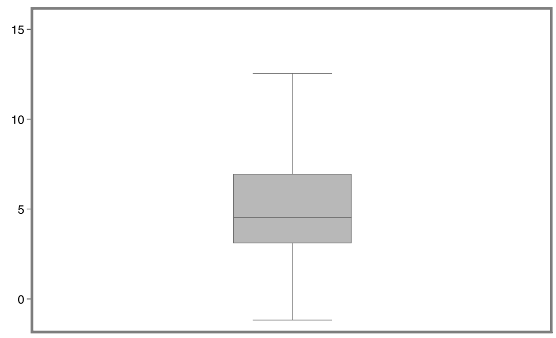


Figure A.3: Box plot independent variable

CP



CD

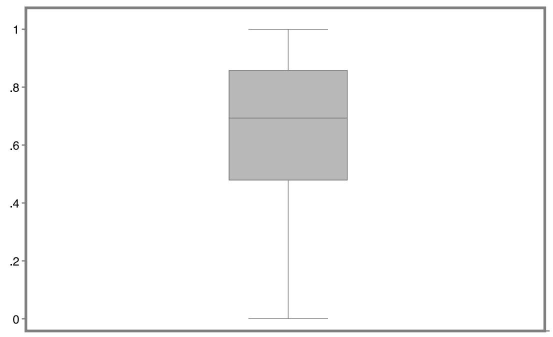
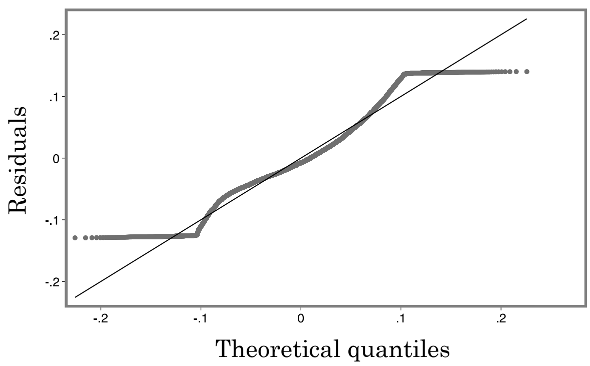
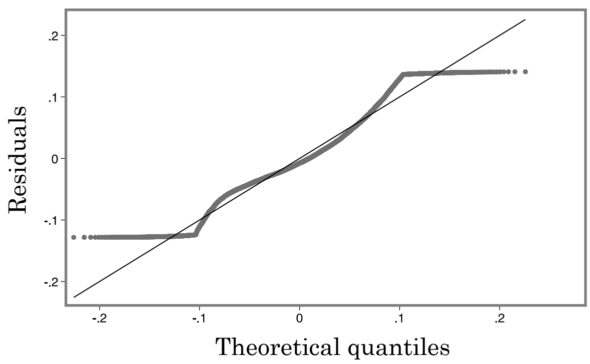


Figure A.4: Q-Q plots

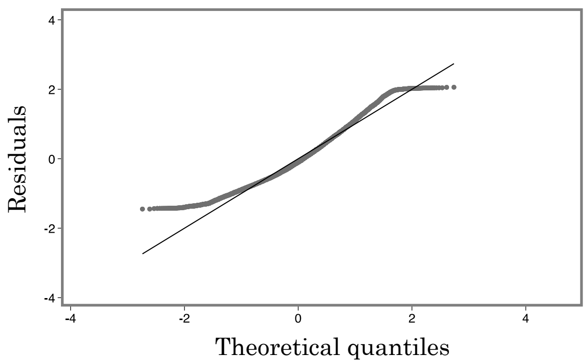
ROA - CP



ROA - CD



Ln Tobin's Q - CP



Ln Tobin's Q - CD

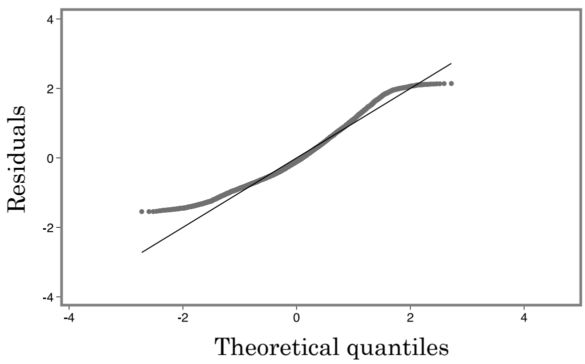


Table A.2: Pearson correlation matrix

The Pearson correlation matrix, indicating the strength and direction of the linear relationship between various financial and operational variables used in the study.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(1) ROA	1.000									
(2) Ln Tobin's Q	0.482*	1.000								
(3) CD	0.018*	-0.116*	1.000							
(4) CP	0.015	0.046*	0.083*	1.000						
(5) CP^2	-0.008	0.001	0.099*	0.965*	1.000					
(6) Size	-0.102*	-0.347*	0.327*	0.550*	0.582*	1.000				
(7) Leverage	-0.221*	-0.142*	0.040*	-0.279*	-0.274*	0.024*	1.000			
(8) R&D intensity	-0.080*	0.342*	-0.022*	0.094*	0.054*	-0.196*	-0.129*	1.000		
(9) Capital intensity	-0.227*	-0.066*	-0.047*	-0.121*	-0.106*	0.029*	0.150*	0.257*	1.000	
(10) Growth	0.241*	0.148*	-0.048*	0.022*	0.005	-0.058*	-0.058*	0.094*	0.013	1.000

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

Table A.3: VIF scores

VIF scores show the extent to which independent variables are linearly correlated with one another. Multicollinearity needs further examination when the VIF score is greater than 5 and is problematic when its higher than 10.

Variables	**(1)**	**(2)**
CP^2	15.570	0.064
CP	15.310	0.065
Size	2.250	0.445
Ln Tobin's Q	1.360	0.734
R&D intensity	1.360	0.738
Capital intensity	1.190	0.839
Leverage	1.170	0.855
CD	1.160	0.862
Growth	1.030	0.973
Mean VIF	4.490	

Variables	**(1)**	**(2)**
Size	2.190	0.457
CP	1.900	0.525
Ln Tobin's Q	1.360	0.736
R&D intensity	1.350	0.741
Capital intensity	1.190	0.840
Leverage	1.160	0.862
CD	1.160	0.862
Growth	1.030	0.974
Mean VIF	1.420	

CP^2 is excluded since it strongly correlated with CP by design

Table A.4: Hausman test for ROA

The Hausman test determines whether the coefficients estimated by the random effects model are consistent and can be preferred over the fixed effects model in panel data analysis.

Variables	FE (b)	RE (B)	Differences (b-B)	Std. err.
CD	0.002	0.008	-0.006	0.001
CP	0.007	0.005	0.002	0.001
CP^2	-0.000	-0.004	0.000	0.000
Size	-0.001	0.002	0.002	0.001
Leverage	-0.147	-0.118	-0.029	0.004
R&D intensity	-0.331	-0.222	-0.109	0.017
Capital intensity	-0.009	-0.008	-0.001	0.001
Growth	0.0536	0.061	-0.007	0.001

	Coef.
Chi-square test value	183.296
P-value	0.000

Table A.5: Hausman test for Ln Tobin's Q

The Hausman test determines whether the coefficients estimated by the random effects model are consistent and can be preferred over the fixed effects model in panel data analysis.

Variables	FE (b)	RE (B)	Differences (b-B)	Std. err.
CD	0.038	0.046	-0.008	0.007
CP	0.006	0.048	-.041	0.005
CP^2	0.003	0.001	0.012	0.000
Size	-0.035	-0.104	0.002	0.009
Leverage	0.095	0.009	-0.069	0.016
R&D intensity	0.289	1.400	0.085	0.098
Capital intensity	-0.083	-0.064	-1.112	0.003
Growth	-0.086	-0.020	-0.066	0.005

	Coef.
Chi-square test value	3,569.660
P-value	0.000

Table A.6: First stage of the IV-2SLS model

Results of the first stage of the IV-2SLS model shows the regression of the endogenous variable on the instrumental variables. The first stage aims to generate predicted values for the endogenous explanatory variables, which is done to remove the variation of these variables that is correlated with the error terms in the regression model. Model H1 and Model H2 study the effect of carbon disclosure, while Model H3 and Model H4 study the effect of carbon performance on financial performance in both the short and long-term.

	Dep: CD	*Dep: CP*
	Model H1 & H2	**Model H3 & H4**
CD Industry mean	0.9942***	
	(0.123)	
CD Country mean	0.6274***	
	(0.032)	
CP Industry mean		0.1179***
		(0.010)
CP Country mean		0.1671***
		(0.013)
CP^2		0.0873***
		(0.001)
Size	0.0310***	-0.0320***
	(0.001)	(0.006)
Leverage	0.0508***	-0.0317
	(0.019)	(0.063)
RD	0.2549***	1.6532***
	(0.047)	(0 .128)
Capital intensity	-0.0155***	-0.0607***
	(0.002)	(0.009)
Growth	-0.0057	0.0954*
	(0.011)	(0.040)
Region dummy	-0.0406***	0.0788***
	(0.003)	(0.012)
Industry dummy	-0.0011	0.0092
	(0.002)	(0.009)
Constant	-0.8469***	1.2159***
	(0.086)	(0.098)

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