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Mandatory emissions reporting and long-run financial performance of listed firms in the UK

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ABSTRACT

Based on arguments derived from the neo-institutional theory, this study investigates the relation between emissions intensity and long-term equity returns in UK listed non-financial firms over a 15-year period (2005-2019). Using mandatory emissions reporting regulation of 2013 as a quasi-natural experiment, we find evidence that there existed a negative association between emissions intensity and long-term equity returns in both high and low emissions industries before the 2013 regulation was implemented. Our results further reveal that the implementation of the aforementioned regulation altered the equity return-emissions intensity relation from negative to positive for high emissions industries, while low emissions industries showed no significant change. This divergence suggests that the 2013 regulation has played a crucial role in reshaping investor expectations by highlighting the exposure of polluting industries to regulatory and litigation risks associated with higher emissions.

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1. Introduction

Increasing recognition of the profound impact greenhouse gas (GHG) emissions have on the dynamics of climate change has inspired several studies to explore the link between GHG emissions and corporate financial performance (CFP). While many studies examine this relationship within the broader context of corporate social responsibility (CSR) and CFP, only a limited few have concentrated on establishing a direct link between a company's GHG emissions and its financial outcomes. Studies of the latter type commonly use annual firm-level GHG emissions expressed in tonnes of CO_2 equivalent (tCO_2e) as the key emissions metric (e.g. see, Baboukardos 2017; Bolton and Kacperczyk 2021; Matsumura, Prakash, and Vera-Munoz 2014), but a small minority (e.g. Ardia et al. 2023; Aswani, Raghunandan, and Rajgopal 2024) uses emissions intensity (EI) as their key emissions variable.

EI is defined as the ratio of annual GHG emissions and corresponding revenues at the firm-level. It is arguably a better metric to measure the environmental impact of a firm as it shows additional emissions (tCO_2e) produced in generating additional revenue (millions). So, a lower EI not only signifies improved environmental performance but also reflects economic efficiency within a firm's production processes. This makes EI a better metric to study microeconomic phenomena like the CFP in comparison with aggregate emissions data. While aggregate emissions data are appropriate for setting national emissions targets, EI is better for assessing firm performance as it incorporates environmental and economic/financial metrics in a single performance measure (Aswani, Raghunandan, and Rajgopal 2024). In other words, EI balances environmental and fiduciary responsibilities of a firm, thus aligns well with the concept of 'just transition.'

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However, the evidence on association between EI and financial returns has been mixed. For example, Ardia et al. (2023) finds lower returns to be associated with portfolios containing firms with lower EI, whereas Aswani, Raghunandan, and Rajgopal (2024) reports no direct relation between EI and CFP at the firm level. Given the paucity of research using emissions intensity to study the economic impact of climate risk, further evidence is required. This study aims to address this issue by studying the impact of EI on CFP in the UK market.

Recent literature on climate risk-CFP nexus has tended to decompose climate risk exposure into its physical and transition components. The distinction between the two is that the former captures the immediate vulnerability to losses caused by climate shifts, while the latter predominantly encompasses the sociopolitical and legal facets. Findings of Faccini, Matin, and Skiadopoulos (2023) suggest that financial markets are increasingly integrating climate transition risk into their assessments, while the impact of increased physical climate risk is not sufficiently reflected in asset prices. This divergence in market behaviour can be attributed to difficulties in pricing physical risks due to their uneven temporal and geographical distribution. In contrast, transition risks are often industry-specific and exhibit a high level of persistence, making them more quantifiable. For instance, energy-intensive sectors such as mining, power generation, and aviation are closely linked to high emissions. Consequently, they face greater exposure to transition risks, as regulations and policies aimed at emissions reduction have a substantial impact on their operations. These distinctions between high emissions and low emissions industries can lead to differences in the strength of the EI-expected returns relation among these industry groups. Therefore, this paper aims also to contribute to the literature by systematically investigating this issue.

A key type of transition risk is that emanating from government intervention, typically in the form of new regulation. For instance, Chen, Hung, and Wang (2018) show that the imposition of mandatory CSR disclosure in 2008 changed behaviour of Chinese listed firms, resulting in decreased profitability, but improvements in environmental performance. Similarly, Ren et al. (2023) find that Chinese firms subject to mandatory CSR disclosure policy of 2008 improved their green innovation performance following the implementation of this policy. We analyse the impact of transition risk by scrutinizing the impact of the Strategic Report and Directors' Report Regulations of 2013 (hereafter, the 2013 regulation) on UK firms.[1] This regulation mandated public disclosure of GHG emissions in annual reports, significantly improving data availability, consistency, and comparability across firms. This creates a quasi-natural experiment to assess the impact of mandatory emissions disclosure on the CFP. Therefore, another key contribution of this study is to provide empirical evidence on the change in the impact of EI on the CFP following the implementation of the mandatory emissions reporting regulation.

EI can influence both cash flow and the discount rate components of CFP. According to Haque and Ntim (2020), neo-institutional theory (NIT) suggests that both social legitimization and economic efficiency impact the CFP. Environmentally friendly firms, by attracting a wider customer base and achieving higher economic efficiency, can enhance their corporate earnings as well as market values. Pástor, Stambaugh, and Taylor (2021) highlight that investor demand for green investments, driven by a need to hedge against climate risks and a preference for sustainability, affects the cost of capital. Accordingly, Ardia et al. (2023) finds that unexpected increase in climate change concerns is associated with increase (decrease) in the discount rate of firms with high (low) EI at both daily and monthly frequencies. However, as effects of climate risk and related mitigation policies typically unfold over extended time horizons, a longer-term perspective is necessary.

Given our focus is on long-term financial performance, we use the cyclically adjusted price-to-earnings ratio (CAPE) to measure CFP. Introduced in Campbell and Shiller (1998), CAPE is regarded as one of the most reliable predictors of long-term equity returns. This ratio, calculated by utilizing a 10-year average of smoothed earnings, effectively mitigates the impact of economic cycles and other short-term fluctuations. It serves as an inverse measure of future returns, a relationship well-established mathematically by Philips and Ural (2016). Since CAPE is immune to short-term earnings fluctuations, it provides insights into a company's long-term performance.

Results of this study are based on panel data drawn from non-financial firms listed on the FTSE 350 index spanning the 2005–2019 period. Using generalized method of moments for estimating dynamic panel data models, our research makes three important contributions to the extant literature. First, our study contributes to the literature examining the effect of environmental performance on corporate financial outcomes. We provide evidence that before the implementation of the 2013 regulation, there existed a statistically significant negative association between EI and long-run expected returns for both high and low emissions industries. This result is robust to the inclusion of industry fixed effects in the model, which hints at investors not differentiating between high and low emissions industries prior to the implementation of the 2013 regulation in the UK. By focusing on long-run prospective returns, our findings both align with and complement Aswani, Raghunandan, and Rajgopal (2024), who found that scaled emissions do not correlate with stock returns. To our knowledge, this is the first study to examine very long-run stock returns that match the duration of the climate transition risk.

Second, our paper contributes to the literature that examines the economic consequences of mandatory emissions disclosure. We find that the sign of the expected returns-EI relation reverses after the implementation of the 2013 regulation. Again, the coefficient obtained is statistically significant but small in magnitude. This result suggests that mandatory disclosure of emissions has material impact on investor perception of climate-related risks. The negative (positive) association between CAPE (long-term expected returns) and EI suggests investors associate higher risk with high carbon intensity firms, resulting in higher expected returns for these firms in the post 2013 period. These findings support the conceptual recommendations of Ngo et al. (2022) who suggest that the climate-related financial disclosures are critical for stimulating sustainable investments, particularly for firms in energy-intensive sectors such as energy, materials and buildings, and transportation.

Third, our paper contributes to the literature by providing evidence that legitimation issues can significantly impact CFP as envisaged by the NIT. Specifically, we find that the implementation of the 2013 regulation changed the expected return-EI relation from negative to positive for high emissions industries but not for low emissions industries. We interpret this divergence as the evidence that the 2013 regulation has been instrumental in altering investor expectations by highlighting greater exposure of high emissions industries to the climate transition risk. These results are also in line with the predictions of Pástor, Stambaugh, and Taylor (2021) which posits that climate-related risks play an important role in shaping portfolio choices made by investors. Therefore, our results advance the literature on the impact of regulatory changes on financial markets and highlight the reallocation of capital across industries prompted by climate change mitigation policies.

Though our study is focused on UK firms, we argue that our results are applicable to other markets, especially those with similar socioeconomic structure. For example, UK regulations during our sample period were closely aligned with the EU regulations, and several European countries are considered UK's peers in terms of their economic development. We further elaborate on this issue in the next section by discussing institutional features of the UK market along with associated theoretical framework and hypothesis development. The rest of our paper is organized as follows. Section 3 describes our research design and data. Section 4 presents and discusses our empirical results, and Section 5 concludes.

2. Institutional background, theoretical framework, and hypothesis development

2.1. The UK regulatory environment

According to the Taskforce on Climate-related Financial Disclosure (TCFD), transitioning to a low-carbon economy entails changes in policy, legislation, technology, and markets. These changes will impact companies' operations especially for those in high emissions industries (TCFD 2017). Accordingly, the UK has set ambitious targets to reduce GHG emissions by at least 68% from 1990 levels by 2030, and to achieve net-zero emissions by 2050. To help achieve these goals, the UK government has implemented various policies and regulations to reduce the carbon emissions of companies, including the Climate Change Act of 2008, the CRC Energy Efficiency Scheme of 2010, and the Industrial Energy Transformation Fund of 2018. One key regulation in this context is the 2013 GHG disclosure regulation mentioned in the preceding section.

The 2013 regulation amended the UK Companies Act 2006 by repealing section 417 of the act and introducing new sections 414A to 414D. The amendment mandates UK listed companies to disclose their global GHG emissions (including CO_2 and other greenhouse gases) at scope 1 and scope 2 levels, but not at the scope 3 level.[2] In other words, companies are required to report direct emissions related to their business operations as well as indirect emissions related to purchased electricity and gas in their annual reports. While several UK firms were disclosing emissions data voluntarily before the implementation of this regulation, it has been instrumental in standardizing the reporting of such data, which in turn has made it easier to compare firms on this metric and has raised stakeholder awareness of availability of these data.

Misani and Pogutz (2015) opine that scope 1 and scope 2 carbon emissions clearly quantify the firm's usage of, and thus implicitly determine costs of, fossil fuels and energy used. Therefore, in accordance with the 2013 regulation, this study uses the sum of scope1 and scope 2 emissions for calculating EI. Additionally, according to the Carbon Disclosure Project (CDP 2018), the UK market has the largest proportion of companies making scope 1 and scope 2 emissions disclosures (> 97%) and the largest proportion of board-level oversight of climate change risks (> 96%). This feature of the UK market makes comparison between pre and post 2013 periods more reliable.

2.2. Theoretical framework

A sizeable literature has explored the link between GHG emissions and the CFP, primarily in the context of CSR policies adopted by businesses and their financial impact. These studies commonly use either the stakeholder theory or the agency theory as the framework to analyse this relation. Haque and Ntim (2020) contend that agency theory is related to economic efficiency of firms whereas the stakeholder theory explains the social/moral aspect of their role in society. They further assert that the neo-institutional theory (NIT) encompasses both economic and social aspects of businesses, hence is better suited to exploring issues straddling both these dimensions of businesses. As explained below, the EI-CFP nexus is related to economic as well as social considerations. Therefore, this paper employs NIT as the framework to inform the analysis.

As GHG emissions correspond directly to the cost of energy used and efficiency of production processes, lower EI is indicative of greater operational efficiency. This observation corresponds to the economic perspective of the NIT and correlates directly with the earnings generated by firms. On the other hand, firms with relatively higher emissions may suffer from a smaller customer base, which can affect their revenues, thereby lowering their earnings, cashflows and dividends. Similarly, investors with environmental concerns are reluctant to include high emissions companies in their portfolios, reducing the share price growth and hence the capital gains associated with investing in such firms. In addition, due to diminished demand for financial securities from high emissions firms, raising new capital in the primary market becomes more expensive for them. Compounding these challenges, high emissions companies face greater exposure to regulatory and litigation risks, which further increase their cost of capital. These issues are related to the social aspect of the NIT. Consequently, under the NIT framework, emissions data can potentially impact equity returns over short as well as long horizons due to their association with both cash flows and the discount rates.

Framing our analysis within the NIT framework is motivated also by the under-theorization observed in studies examining the relationship between corporate carbon and financial performance (Velte, Stawinoga, and Lueg 2020). We contend that grounding our results in NIT will enhance the comparability of our findings with research exploring the connection between emissions disclosure and its financial implications, including value relevance, information asymmetry, financial performance, and cost of capital.

2.3. Hypothesis development

2.3.1. GHG emissions and the CFP

A vast body of literature focuses on exploring links between firms' ESG scores and their financial performance. However, there are some limitations associated with using composite ESG scores for studying this relation. First, ESG ratings are inherently noisy, aggregating multiple indicators across three pillars (E, S and G) with variations in scopes, measurements, and weights among different data providers, such as Refinitiv, MSCI, Morningstar, and Sustainalytics (Berg, Koelbel, and Rigobon 2022). Moreover, ESG rating providers often utilize industry-adjusted pillar scores to evaluate corporate ESG performance. It is a significant issue also because a company's exposure to climate risk is significantly influenced by the industry in which it operates (Unerman and O'Dwyer 2007). Though climate-related factors are significant contributors to overall ESG scores, their contribution is relatively small. These considerations necessitate the use firm-level emissions to explore the link between emissions and CFP to provide reliable tests of this relationship.

Carbon emissions usually serve as a key indicator for assessing a company's environmental impact. The concept of corporate carbon risk can be divided into two primary metrics: absolute and relative (Busch and

Lewandowski 2018; Hoffmann and Busch 2008). The absolute metric quantifies a company's direct impact on climate change by measuring its emissions in terms of carbon equivalents across different scopes including Scope 1, Scope 2, Scope 3, or their total (Clarkson et al. 2015; Delmas, Nairn-Birch, and Lim 2015; Griffin, Lont, and Sun 2017; Matsumura, Prakash, and Vera-Munoz 2014). In contrast, the relative metric, often referred to as 'carbon intensity,' relates these absolute emissions figures to financial indicators like revenues or total assets, thus providing a scaled measure of carbon equivalents in relation to its size (Harangozo and Szigeti 2017; Hoffmann and Busch 2008; Qian and Schaltegger 2017).

Few recent papers have explored the relationship between absolute carbon emissions and CFP, but their findings are mixed. For example, Griffin, Lont, and Sun (2017) and Matsumura, Prakash, and Vera-Munoz (2014) find that higher emissions are associated with a lower market value, while Bolton and Kacperczyk (2021) observe a positive relation between emissions and stock returns. Similarly, Delmas, Nairn-Birch, and Lim (2015) finds a negative relation between corporate environmental performance and return on assets but a positive relation between improvements in environmental performance and Tobin's q. A meta-study by Busch and Lewandowski (2018) suggests that carbon emissions vary inversely with financial performance, with market-based measures of financial performance exhibiting a stronger relation than accounting-based measures. As such, these diverse results can be attributed to the wide range of methods employed and the diverse set of indicators utilized to measure both emissions and CFP, as well as moderating factors such as industry and country characteristics.

Carbon intensity is arguably a more refined metric for assessing carbon risk because it not only provides insights into a company's emissions relative to its economic output, but also aligns with societal objectives to reduce emissions (environmental impact) while maintaining economic productivity (Hoffmann and Busch 2008; Nordhaus 2019). However, studies using carbon intensity to explore emissions-CFP relation are rare and their results have been mixed. For instance, Aswani, Raghunandan, and Rajgopal (2024), and Bolton and Kacperczyk (2021) find no significant association between CFP and carbon intensity, while Busch and Lewandowski (2018) suggest that relative emissions are more likely to produce statistically significant results than absolute emissions.

Irrespective of their divergent empirical findings, these studies contend that companies with higher carbon intensity are likely to face increased financial risks. These risks stem from potential regulatory fines, increased expenses due to carbon taxes, and a potential degradation in the company's reputation among its stakeholders. Therefore, investors could associate higher EI with higher risk and thus demand a higher return for investing in such firms. Based on these arguments, we formulate our first hypothesis as:

Hypothesis 1: Other things being equal, higher EI is associated with higher expected long-term equity returns.

In other words, we expect a significant negative relationship between EI and CAPE.

2.3.2. *Industry affiliation and the CFP*

Our study also relates to the strand of literature exploring the link between climate change-related disclosure practices, particularly those based on the TCFD's recommendations, and their financial impact. Since emissions data can be used to assess and manage relevant climate-related risks and opportunities, our study focuses specifically on target and metrics dimension of these recommendations. For instance, Ngo et al. (2022) suggest that adhering to the TCFD's guidelines is feasible for firms in energy-intensive sectors such as energy, materials and buildings, and transportation. Similarly, Maji and Kalita (2022) find a positive relation between TCFD-based climate disclosures and financial performance in the firms operating in India's energy sector.

It is well known that few industries, e.g. mining, oil and gas extraction, paper and allied products, chemicals and allied products, petroleum refining, metals, electric, gas, and sanitary services, account for a large share of GHG emissions. Prior research suggests that these industries are likely to have a greater exposure to the climate risk. For instance, Hsu and Wang (2013) contend that firms from polluting industries are in general exposed to higher environmental costs, along with increased political pressure from regulators and environmentalists. Supporting this view, Galama and Scholtens (2021) find a significant association between corporate GHG emissions and financial performance, noting that a firm's industry affiliation influences this relationship. Using a sample of US firms, Griffin, Lont, and Sun (2017) finds that firms with higher GHG emissions levels have a negative correlation with stock prices, and this relationship is more pronounced for carbon-intensive companies.

This finding is consistent with Busch and Hoffmann's (2011) research, which suggests that financial markets are responding to increased corporate reporting of GHG emissions by devaluing firms with higher carbon intensity, as investors become increasingly concerned about the potential financial risks associated with climate change. Similarly, Konar and Cohen (2001) find that reduction in emissions of toxic chemicals increases market value of listed US firms, and that the magnitude of these effects differs across industries.

In contrast, low EI industries, such as technology, professional services etc., face considerably lower carbon risks. These industries are often less intertwined with direct environmental impacts and have a smaller carbon footprint, leading to fewer visible environmental concerns. Not only this, companies within high emissions industries are often burdened with short-term increases in operational costs related to climate change and carbon reduction, manifesting in various forms, such as waste management expenses and the costs associated with implementing emissions-reducing technologies. While these investments promise both environmental and financial returns, the benefits aren't immediate. This, in turn, leads to higher initial financial risks for these industries compared with their less-polluting counterparts (Busch and Hoffmann 2011; Eleftheriadis and Anagnostopoulou 2015). Moreover, polluting companies are under heightened scrutiny from regulatory agencies focused on environmental protection. Accordingly, Hsu and Wang (2013) suggest that non-compliance tarnishes firms' reputation and exposes them to substantial financial penalties and potential legal sanctions.

The evidence discussed above suggests that high emissions industries are subjected to significantly higher stakeholder pressure and regulatory scrutiny. Therefore, if the market demonstrates varying sensitivities to carbon risk across high and low-emissions industries, then investors' perception of carbon risks is expected to be more pronounced for companies within industries in the high emissions category. As companies from high emissions industries are more likely to be penalized by the market for poor environmental practices, our second hypothesis can be stated as follows:

Hypothesis 2: The relationship between expected long-term equity returns and EI is moderated by firms' industry affiliation.

Therefore, the magnitude of the negative association between EI and CAPE is expected to be larger for firms within high emissions industries.

2.3.3. Mandatory emissions reporting, industry affiliation, and the CFP

A well-developed strand of literature distinguishes between the impact of voluntary and mandatory disclosure regimes on financial markets. For instance, Bertomeu, Vaysman, and Xue (2021) suggest that well-designed mandatory disclosure policies often involve conservative reporting of bad news and can serve as effective substitutes for voluntary disclosures. This is because mandatory disclosures create additional social value by controlling the extent of bad news reported. Conversely, studies such as Kim (2014) report positive impact of voluntary reporting on firm value and find that the imposition of mandatory regulations is associated with negative valuation effects across the market. These conflicting results suggest that the impact mandatory emissions reporting has on expected returns remains an empirical issue.

In the same vein, the research on the economic impact of carbon disclosure has been rather limited and the results reported in these studies have been conflicting. For example, using a sample drawn from S&P 500 constituent firms, Matsumura, Prakash, and Vera-Munoz (2014) find that markets penalize all firms for their carbon emissions, but this penalty is greater for firms that do not voluntarily disclose their emissions. On the other hand, Griffin, Lont, and Sun (2017), also using a sample of S&P 500 firms, report that GHG emissions have a negative impact on equity values, but this valuation discount does not differ between firms that disclose their emissions using the CDP and those that do not. They suggest that markets impound GHG emissions into equity prices, but their source of information is not the CDP. It is plausible that data provided by databases such as MSCI, Refinitiv and S&P Global, could be the source of this information, as these are commonly used both in industry as well as in academia. However, mandatory reporting of emissions data should harmonize the data available across all data sources.

For instance, under the 2013 regulation, companies are mandated to report their carbon footprint according to structured formal calculation and reporting rules (Sullivan and Gouldson 2012). de Villiers and van Staden (2011) contend that mandatory disclosure enhances the quality and reliability of companies' carbon emissions data, making it easier for investors to assess the carbon risks associated with different companies. While several UK firms were disclosing emissions data voluntarily before the implementation of the 2013 regulation, it has been instrumental in standardizing the reporting of such data, which in turn has made it easier to compare firms on this metric and has raised stakeholder awareness of availability of these data. In the same vein, Andrew and Cortese (2011) argue that it remains unclear whether investors perceive non-financial environmental information, such as carbon emissions, differently under mandatory disclosure frameworks as opposed to voluntary ones. Therefore, the UK's 2013 regulation provides a quasi-natural setting to assess the impact public dissemination of this information has on the financial performance of businesses. To leverage this setting, we formulate our third hypothesis as:

Hypothesis 3a: The implementation of the 2013 regulation altered the strength of association between EI and expected long-term equity returns.

In the past, companies with high carbon emissions could shift the costs of those emissions onto others and avoid exposure to carbon risk (Andersson, Bolton, and Samama 2016). Subsequently, with the increasing number of initiatives aimed at reducing carbon emissions, such as carbon taxes and carbon emissions trading schemes, companies are now obligated to internalize the costs of their emissions (World Bank n.d.). Consequently, transition risk has become a crucial consideration for businesses. Notably, policies aimed at climate change mitigation and abatement invariably target high emissions industries. For example, UK's carbon price floor regulation of 2013 targets high emissions industries such as energy production and aviation. Therefore, if the market responds to the 2013 mandatory emissions disclosure regulation as proposed in the preceding hypothesis, we expect polluting firms to experience a greater impact, given their heightened susceptibility to carbon disclosure. Taking the industry affiliation effect into account, we formulate a corollary to the previous hypothesis as follows:

Hypothesis 3b: The implementation of the 2013 regulation impacts the relationship between the expected long-term equity returns and EI differently for firms from low and high emissions industries respectively.

3. Research design

3.1. Data and variables

This study uses unbalanced panel data drawn from non-financial firms listed on the UK's FTSE350 index from 2005 to 2019 period. Firms within the FTSE 350 index represent the United Kingdom's largest businesses by market capitalization, thereby serving as indicators of the nation's economic performance and the effectiveness of its carbon mitigation strategies. Furthermore, this timeframe assumes critical importance as it encompasses the implementation of the 2013 Regulation, affording insights into whether mandatory carbon emissions disclosure significantly influences market-driven corporate valuation. Since the calculation of CAPE requires annual data from previous 10 years, the earnings and revenue data used for this calculation were obtained for 1996–2019 period.

As the dependent variables used in our study require at least ten years of earnings and revenues data, so only the firms meeting these criteria are included in the sample. The GDP deflator data used for calculating seasonally adjusting earnings and revenues are obtained from the World Bank website. All other variables used in the study are sourced from Refinitiv. To avoid high correlation between data vendor estimated emissions and financial variables, only the voluntarily disclosed emissions data are used for calculating EI before the 2013 regulation was enforced.[3] After discarding firms with missing variables and observations with missing values, the final sample contains 127 firms and 1007 firm-year observations.

3.1.1. Dependent variable

As mentioned before, we use CAPE as a proxy for long-term market-expected financial returns. The CAPE ratio is a useful predictor of future stock market returns. In general, a high CAPE ratio suggests that the stock prices are overvalued and may be due for a correction and future stock market returns are expected be lower than average, while a low CAPE ratio suggests that the market undervalues the share and future stock market returns will be higher to match their long-term average (Philips and Ural 2016). Additionally, the CAPE ratio incorporates information about the long-term profitability of companies, minimizes the impact of economic cycles and other fluctuations (using the average earnings over a ten-year period) and captures the overall trend in corporate earnings and operational capabilities, providing a clearer picture of a company's true value (Siegel 2016). All other things being equal, a lower CAPE should yield higher equity returns.

Mathematically, CAPEe (CAPEr) is defined as the ratio of a company's share price to the ten-year average of its inflation-adjusted earnings per share (revenues per share). Following Philips and Ural (2016), CAPEe is calculated as:

$$CAPEe_{i,t} = CP_{i,t} \times \left[\frac{1}{n} \sum_{i=0}^{n-1} (GDEF_t \times GDEF_{t-i}^{-1}) E_{t-i} \right]^{-1} \tag{1}$$

In Equation (1), the numerator CP is the annual closing share price of each firm included in our sample, while the denominator is the rolling ten-year average of their real earnings per share (EPS). GDEF represents the GDP deflator. Philips and Ural (2016) suggest also using other flow variables such as revenues for calculating CAPE. Accordingly, to calculate revenues per share (RPS) based CAPE (i.e. CAPEr) we substitute the EPS with the RPS, and then Equation (1) can be reformulated as:

$$CAPEr_{i,t} = CP_{i,t} \times \left[\frac{1}{n} \sum_{i=0}^{n-1} (GDEF_t \times GDEF_{t-i}^{-1}) Rev_{t-i} \right]^{-1} \tag{2}$$

In Equation (2), the denominator is the ten-year average of each stock's real revenues per share (denoted as Rev), adjusted by the corresponding GDP deflator.

3.1.2. Independent variables

EI, the key explanatory variable used in this study, is calculated as the annual ratio of the sum of scope 1 and scope 2 emissions (total emissions) and total revenues. It's important to note that GHG emissions differ considerably across industries, making the reduction of these emissions to diminish the carbon footprint and mitigate climate change particularly important in polluting industries mentioned before. To alleviate industry bias, we use an alternative metric SEI that benchmarks a firm's carbon emissions against others in the same industry. Specifically, the approach involves dividing the difference between an individual company's carbon intensity and the industry-year average intensity by the industry's standard deviation of carbon intensity.

Additionally, this paper includes four firm-specific control variables in the analysis: market beta (Beta), firm size (Size), financial leverage (LEV), and intangible assets to total revenues (IAR). Beta controls for time-varying sensitivity of a firm's returns to market risk. It is estimated by running 5-year rolling-window time series regressions of firm level excess returns on excess returns of FTSE350 index over our sample period. As beta is related positively to returns, it is expected to be negatively correlated with CAPE.

Since firm size is also an important predictor of a firm's expected returns, we include the natural logarithm of total assets as proxy for size. It is known to be negatively associated with returns, so we expect a positive relation between this variable and CAPE. Financial leverage is the ratio of the long-term debt to common equity and controls for shareholders' exposure to financial risk. Firms with greater exposure to financial risk are expected to provide higher returns, therefore, we expect a negative relation between LEV and CAPE. In addition, a company with high levels of leverage may face financial constraints that limit its ability to invest in sustainability measures, including reducing its GHG emissions.

Last, but not the least, investment in research and development (R&D) is a crucial factor in determining the relationship between environmental performance and corporate financial performance and it can be seen as a signal of the environmental responsiveness of the firm to the market (McWilliams and Siegel 2000). Due to the dearth of R&D expenditure data availability at the firm level for our sample, we follow the example of Elsayed and Paton (2005) and use total intangible assets to total revenues ratio (labelled IAR) to proxy for the effect of the R&D investment. Prior research, such as Hirshleifer, Hsu, and Li (2013), has shown innovation efficiency to be positively related to future returns, therefore, we expect a negative association between CAPE and IAR.

Additionally, IAR provides insight into the composition of a company's assets and the degree to which intangible assets contribute to its overall value.

3.2. Model and methodology

As CAPE is based on the average of past adjusted earnings, it exhibits significant autocorrelation, necessitating the use of dynamic panel data modelling. Unobserved heterogeneity is also a common concern in microeconomic data like the one used in this study. Presence of temporal persistence and unobserved heterogeneity is known to cause bias in coefficient estimates and standard errors obtained using pooled OLS, fixed effects, and random effects regressions. In contrast, variants of the generalized method of moments (GMM) estimation methodology described in Arellano and Bond (1991); Arellano and Bover (1995) and Blundell and Bond (1998) do not suffer from these issues, hence are deemed appropriate estimation methods to use in this study. It is so because when applied to dynamic panel data models, GMM effectively handles challenges like endogeneity, heteroskedasticity, and serial correlation (Baum and Mark 2007).

The primary source of endogeneity in our model is the use of lagged dependent variables as explanatory variables. To ensure consistent and efficient parameter estimation in presence of endogeneity, we employ the two-step system GMM (SYSGMM) procedure of Blundell and Bond (1998). SYSGMM is chosen because it combines the advantages of the first-differenced GMM (the Arellano-Bond estimator) and the level GMM (Arellano and Bover 1995 and Blundell and Bond 1998 estimator) for more efficient estimation. In addition to original variables, these regressions use transformed variables that can be instrumented using the lags of the original regressors. For original variables, their first differences are used as instruments. For this scheme to work effectively, the transformation should render the transformed variables minimally dependent on lagged observations of the original variables so that the latter can be used as valid instruments (Roodman 2009). Since our sample is an unbalanced panel, we use 'forward orthogonal deviations' to generate the transformed variables, as recommended by Arellano and Bover (1995), in order to maximize our sample size. Finally, a Hansen test of overidentification is conducted to confirm the validity of the instrument set used in each regression.

To test the first hypothesis the following dynamic panel regression model is formulated:

$$CAPE_{i,t} = \alpha + \sum_{j=1}^{2} \gamma_j CAPE_{i,t-j} + \beta_2 EI_{i,t} + \beta_3 LEV_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Size_{i,t} + \beta_6 IAR_{i,t} + \beta_7 Year_t + \beta_8 Ind_i + \boldsymbol{\varepsilon_{i.t}} \tag{3}$$

Subscript i indexes the firm while subscript t denotes time (year). Here, $CAPE_{i,t}$ is assumed to be a function of its past q lags. EI is the main independent variable of interest, while the control variables used in the model are as described above. $Year_t$ controls for temporal fixed effects and $\mathrm{Ind_i}$ accounts for the industry-specific fixed effects.α represents the intercept term and $\boldsymbol{\varepsilon_{i.t}}$ is the error term. We also test an alternative specification which replaces *EI* with industry-year standardized EI (labelled *SEI*), which considers industry-specific adjustments.

To capture the differences in the CFP-EI relation between low and high emissions industries as per hypothesis 2, we augment Equation (3) by introducing an indicator variable labelled *ES*[4] and its interaction with *EI*. The resulting regression model is shown in Equation (4):

$$CAPE_{i,t} = \alpha + \sum_{j=1}^{2} \gamma_j CAPE_{i,t-j} + \beta_2 ES_i + \beta_3 EI_{i,t} + \beta_4 ES_i \times EI_{i,t} + \beta_5 LEV_{i,t} + \beta_6 Beta_{i,t} + \beta_7 Size_{i,t} + \beta_8 IAR_{i,t} + \beta_9 Year_t + \boldsymbol{\varepsilon_{i.t}} \tag{4}$$

The industry dummy variable, Ind, is not included in Equation (4) because another industry-based dummy variable, *ES*, is added to test for industry effects.

To test the effect of the 2013 regulation on the relationship between EI and CFP as per hypothesis 3a we include an indicator variable labelled GHGeR, which takes value 1 for the period following the implementation

Table 1. Descriptive statistics.

	N	Mean	Median	Std.dev.	Min	Max
CAPEe	1085	19.10	17.11	9.95	5.33	41.52
CAPEr	1085	20.17	18.02	10.43	5.89	43.33
SEI	1085	−0.06	−0.32	0.8	−1.44	2.28
EI	1085	225.10	62.34	407.72	2.11	3747.00
LEV	1085	74.71	51.72	73.65	3.17	302.53
Size	1085	8.44	8.26	1.55	4.15	12.93
Beta	1085	0.96	0.91	0.33	0.36	1.87
IAR	1085	0.123	0.04	0.223	0.00	1.46

of the said regulation and 0 otherwise. An interaction term of GHGeR and EI is also added to capture the changes in EI-CFP relation between pre and post implementation periods.

$$CAPE_{i,t} = \alpha + \sum_{j=1}^{2} \gamma_j CAPE_{i,t-j} + \beta_2 GHGeR + \beta_3 EI_{i,t} + \beta_4 GHGeR \times EI_{i,t} + \beta_5 LEV_{i,t} + \beta_6 Beta_{i,t} + \beta_7 Size_{i,t} + \beta_8 IAR_{i,t} + \beta_9 Ind_i + \boldsymbol{\varepsilon_{i.t}} \quad (5)$$

To test hypothesis 3b, we split our sample between low and high emissions industries and run the model presented in Equation (5) again.

4. Empirical results

4.1. Descriptive statistics

Table 1 provides descriptive statistics for the variables used in the empirical analysis. CAPEe with mean of 19.10 and a standard deviation of 9.95 shows lower mean and variability than CAPEr with a mean of 20.17 and a standard deviation of 10.43. EI has a mean of 225.1 tonnes per million pounds of revenue and a median of 62.34. These values suggest that the distribution of EI is skewed to the right and some firms and industries have significantly higher EI than others. As the average of the industry-adjusted EI (SEI) is close to zero (−0.06), there appears to be much smaller intra-industry variation in EI. In contrast, EI demonstrates a significantly greater degree of variability with a standard deviation of 407.72. An average firm in our sample has a market beta of 0.96, but the riskiness of the firms varies markedly from a minimum beta of 0.36 to a maximum of 1.87. The average firm size in the log form is 8.44, which corresponds to approximately £ 4.6 billion in asset value. Moreover, the average leverage ratio (LEV) is 74.71% with a large variation across firms from a minimum of 3.17% to a maximum of 302.53%. The average IAR (total intangible assets to total revenues ratio) is 0.123, but it varies considerably across firms with a standard deviation of 0.223.

Table 2 presents the correlation matrix for variables used in the analyses. In line with expectations, both estimates of carbon risk (EI and SEI) are negatively correlated with CAPE. In addition, Beta and LEV too are correlated with CAPE with the predicted negative signs, while firm size has negative correlation with CAPE, which is contrary to expectations. Since none of the explanatory variables exhibited a bivariate correlation coefficient greater than 0.5 in magnitude, multicollinearity is not a significant concern in our subsequent analysis.

4.2. Multivariate regressions

Tables 3–5, present results obtained using GMM estimation of dynamic panel data specifications described in the preceding section. For statistical consistency, system GMM requires the presence of first-order serial correlation but no second-order serial correlation. This is the case for all three of our models if (and only if) we include two lags of the dependent variable. Additionally, in each case, the Hansen test of over-identifying restrictions provides support for our choice of instrument set.

The regression results pertaining to hypothesis 1 are presented in Table 3, where the relationship between EI and CAPE is investigated over entire sample period. Columns 1 and 2 report results obtained by regressing

Table 2. Pearson's correlation coefficients.

	CAPEe	CAPEr	SEI	EI	LEV	Size	Beta
CAPEr	0.997***	1					
SEI	−0.060**	−0.063**	1				
EI	−0.133***	−0.130***	0.297***	1			
LEV	−0.097***	−0.094***	0.128***	0.073**	1		
Size	−0.319***	−0.315***	0.096***	0.295***	0.087***	1	
Beta	−0.193***	−0.199***	0.048	0.195***	−0.137***	0.090***	1
IAR	0.001	0.003	0.007	−0.068**	0.032	0.066**	0.012

Table 3. The impact of emissions intensity on CAPE.

	CAPEe		CAPEr	
	(1)	(2)	(3)	(4)
$CAPEe_{t-1}$	0.783***	0.869***		
	(7.54)	(10.32)		
$CAPEe_{t-2}$	0.135	0.058		
	(1.39)	(0.51)		
$CAPEr_{t-1}$			0.778***	0.872***
			(7.63)	(10.94)
$CAPEr_{t-2}$			0.152	0.061
			(1.54)	(0.67)
EI	0.003**		0.003**	
	(2.24)		(2.07)	
SEI		0.612		0.621
		(1.37)		(1.27)
LEV	−0.007	−0.007	−0.007	−0.007
	(−1.24)	(−1.40)	(−1.31)	(−1.40)
Size	−0.772***	−0.700**	−0.720**	−0.719***
	(−2.89)	(−2.51)	(−2.54)	(−2.61)
Beta	−1.209	−1.208	−1.220	−1.068
	(−1.12)	(−0.96)	(−1.04)	(−0.81)
IAR	0.438	1.103	0.091	0.903
	(0.37)	(0.76)	(0.07)	(0.58)
Intercept	11.354***	10.722***	10.969***	10.821***
	(3.56)	(2.89)	(3.29)	(2.97)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
p-value of AR (1) Test	0.001	0.001	0.001	0.001
p-value of AR (2) Test	0.478	0.628	0.211	0.257
Hansen test	0.491	0.563	0.419	0.338
Observations	1,007	1,007	1,007	1,007
Number of firms	127	127	127	127

Notes: This table presents results of dynamic panel GMM regressions outlined in Equation (3). CAPEe and CAPEr are the two dependent variables representing each firm's long-run financial performance. EI represents emissions intensity and is the key explanatory variable. SEI represents standardized EI values based on each firm's industry affiliation. LEV accounts for financial leverage and Size is defined as the log of total assets. Beta represents the market beta for each firm and the label IAR is the ratio of intangible assets to revenue. ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively. T-statistics are given in parentheses.

CAPEe on EI as well as its industry-adjusted version SEI. For robustness, the same set of regressions are repeated for CAPEr and are reported in columns 3 and 4.

Table 3 confirms that all CAPE estimates are positively associated with EI. To be more specific, the regression coefficients for EI in columns 1 and 3 are 0.003 for both CAPEe and CAPEr, significant at 5% level. It indicates that unit increase in emissions intensity leads to an increase of 30 basis points in CAPE. Notably, these results are obtained after including industry fixed effects in regressions. Since CAPE is an inverse indicator of future returns, an increase in CAPE suggests lower expected equity returns or an upward price correction in the future. These results accord with the findings of Ardia et al. (2023), but are opposite to the postulates of hypothesis 1,

Table 4. EI and CAPE – Difference between high and low emissions industries.

	CAPEe		CAPEr	
VARIABLES	(1)	(2)	(3)	(4)
$CAPEe_{t-1}$	0.805***	0.862***		
	(8.03)	(11.58)		
$CAPEe_{t-2}$	0.146	0.096		
	(1.46)	(1.21)		
$CAPEr_{t-1}$			0.797***	0.862***
			(7.93)	(12.12)
$CAPEr_{t-2}$			0.156	0.093
			(1.51)	(1.08)
ES	0.373	−0.707	0.401	−0.789
	(0.37)	(−1.57)	(0.41)	(−1.61)
EI	0.014*		0.015**	
	(1.93)		(2.02)	
ES × EI	−0.011		−0.013*	
	(−1.59)		(−1.78)	
SEI		1.344		1.817**
		(1.60)		(2.13)
ES × SEI		−1.478		−2.376
		(−1.06)		(−1.63)
LEV	−0.008*	−0.009*	−0.010**	−0.010*
	(−1.68)	(−1.68)	(−1.97)	(−1.81)
Size	−0.409	−0.316	−0.333	−0.331
	(−1.26)	(−1.15)	(−0.97)	(−1.08)
Beta	−0.965	−0.301	−1.108	−0.188
	(−0.96)	(−0.27)	(−0.94)	(−0.16)
IAR	0.401	1.102	0.053	1.226
	(0.23)	(0.61)	(0.03)	(0.65)
Intercept	7.278**	7.297**	6.945**	7.622**
	(2.29)	(2.33)	(2.09)	(2.26)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No
p-value of AR (1) Test	0.002	0.002	0.000	0.000
p-value of AR (2) Test	0.540	0.673	0.305	0.342
Hansen test	0.498	0.533	0.384	0.356
p-value of χ^2-Test	0.098	0.154	0.077	0.087
Observations	1,007	1,007	1,007	1,007
Number of firms	127	127	127	127

Notes: This table presents results of dynamic panel GMM regressions outlined in Equation (4). ES is an indicator variable that takes value 1 for polluting industries and 0 otherwise. ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively. T-statistics are given in parentheses. The *p*-values of Hansen test for instrument validity and χ^2-test for the joint significance of ES, EI(SEI) and their interaction term are reported at the bottom of the table.

which suggests that the market expects higher returns from companies with a relatively high carbon intensity. Moreover, when cross-industry differences in emissions and the use of varying emissions metrics are not considered, our results align also with the findings of Bolton and Kacperczyk (2021), who report a positive relationship between unscaled emissions and stock returns.

Interestingly, in columns 2 and 4 of Table 3, coefficients of SEI (industry-adjusted emissions intensity) are not significant statistically at conventional levels. Taken together, results reported in Table 3 suggest that markets don't differentiate between firms belonging to the same industry based on EI, but there is a small difference in the impact of EI on expected returns across industrial sectors. This issue is examined further in results presented in Table 4. Overall, these results conform to the findings of Aswani, Raghunandan, and Rajgopal (2024) who also report no statistically significant association between stock returns and EI.

Estimates for the specification testing for differences in the relationship between EI and CAPE across high and low emissions industries as per hypothesis 2 are shown in Table 4. The main parameters of interest are ES (an indicator for high emissions industries) and its interaction terms. The coefficient on ES measures the difference in intercept between environmentally sensitive (polluting) industries and their non-environmentally

Table 5. The impact of 2013 GHG emissions reporting regulation on EI – CAPE Relation.

	CAPEe			CAPEr		
VARIABLES	(1) Full sample	(2) ES group	(3) Non-ES group	(4) Full sample	(5) ES group	(6) Non-ES group
$CAPEe_{t-1}$	0.571***	0.475***	0.671***			
	(7.05)	(6.64)	(8.36)			
$CAPEe_{t-2}$	0.248***	0.292***	0.093			
	(3.87)	(2.85)	(1.07)			
$CAPEr_{t-1}$				0.573***	0.482***	0.657***
				(7.24)	(4.59)	(7.60)
$CAPEr_{t-2}$				0.234***	0.295***	0.080
				(3.77)	(3.09)	(0.97)
GHGeR	1.365***	0.602	1.831***	1.949***	1.232	2.239***
	(2.88)	(0.67)	(2.58)	(4.34)	(1.43)	(3.09)
EI	0.002*	0.002**	0.005	0.002*	0.002**	0.006
	(1.90)	(2.12)	(1.54)	(1.73)	(2.33)	(1.44)
GHGeR×EI	−0.004**	−0.003**	−0.002	−0.005**	−0.003*	−0.002
	(−2.09)	(−1.99)	(−0.48)	(−2.29)	(−1.87)	(−0.39)
LEV	−0.013**	−0.015	−0.007	−0.014**	−0.018	−0.009
	(−2.16)	(−1.16)	(−1.02)	(−2.21)	(1.31)	(1.07)
Size	−1.478***	−0.763	−2.396***	−1.527***	−0.626	−2.744***
	(−2.97)	(−0.97)	(−4.13)	(−3.09)	(−0.66)	(−3.29)
Beta	−1.500	−3.379	−0.289	−1.752	−3.483	−0.906
	(−1.31)	(−1.32)	(−0.15)	(−1.41)	(−1.43)	(−0.44)
IAR	0.382	3.020	−0.885	0.028	1.844	−0.822
	(0.24)	(0.75)	(0.22)	(0.02)	(0.34)	(0.23)
Intercept	15.694***	14.450*	23.836***	16.233***	12.851	26.770***
	(3.09)	(1.69)	(4.20)	(3.09)	(1.35)	(3.76)
Year fixed effects	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
p-value of AR (1) Test	0.001	0.037	0.000	0.001	0.031	0.000
p-value of AR (2) Test	0.147	0.525	0.360	0.149	0.483	0.366
Hansen test	0.125	0.996	0.974	0.124	0.986	0.969
p-value of χ^2-Test	0.001	0.047	0.006	0.000	0.033	0.000
Observations	1,007	456	551	1,007	456	551
Number of firms	127	54	73	127	54	73

Notes: This table presents results of dynamic panel GMM regressions outlined in Equation (5). GHGeR is an indicator variable that takes value 1 for year 2013 or later and 0 otherwise. ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively. T-statistics are given in parentheses. The *p*-values of Hansen test for instrument validity and χ^2-test for the joint significance of GHGeR, EI and their interaction term are reported at the bottom of the table.

sensitive (non-polluting) counterparts, whereas the coefficients on ES×EI and ES×SEI capture the difference in the impact of carbon intensity on CAPE between the two industry groups.

First, we notice that the coefficient on EI remains positive and significant in both columns 1 and 3 (0.014, $p = 0.054$ and 0.015, $p = 0.043$, respectively). This result is consistent with the findings presented in Table 3. However, the result for SEI shown in column 4 is different from Table 3. The coefficient of SEI (1.817, $p = 0.033$) turns out to be significant when the ES dummy is included in the regression. It is a perplexing result, but being a solitary significant estimate, this result is not generalizable. Moreover, none of the ES coefficients are themselves significant in any regression, so markets do not seem to distinguish between high and low emissions industries. The divergence in results reported in Tables 3 and 4, respectively, can be due to differences in the specifications used in each case. To be precise, Table 3 controls for the differences across industries by including industry fixed effects whereas Table 4 does not. Overall, these findings do not support the notion that the association between carbon intensity and CAPE is stronger for firms from high emissions industries.

Next, we present the results for the specification shown in Equation (5) which tests whether the introduction of the 2013 regulation altered the strength of association between emissions intensity and CAPE. As explained before, GHGeR is an indicator variable that takes value 1 after implementation of the 2013 regulation and 0 otherwise. The coefficients corresponding to GHGeR, EI and their interaction terms are significant in columns

1 and 4 of Table 5. Importantly, the interaction terms have negative coefficients suggesting the 2013 regulation altered the sign of relation between expected returns and EI. While before the implementation of this regulation there existed a positive (negative) association between CAPE (expected returns) and EI, it changed sign after this regulation came into force. The sum of coefficients on EI and the interaction term GHGeR×EI (0.002–0.004 = -0.002 for CAPEe, and 0.002–0.005 = -0.003 for CAPEr, respectively) suggests that the net effect of the implementation of the 2013 regulation is to change the sign of relation between EI and both CAPE estimates. So, commensurate with their greater exposure to climate transition risks, higher EI firms are expected to generate higher returns in the post-2013 period. We interpret this result as the evidence that the 2013 regulation has been instrumental in changing investors' risk perceptions.

To gain deeper insight into this issue, we split the full sample into high (ES) and low emissions (Non-ES) industry groups and re-estimated the specification of Equation (5). The results of these regression are reported in columns 2, 3, 5 and 6 of Table 5. We observe that the interaction term (GHGeR × EI) is significant only for the high emissions (ES group) in columns 2 and 5, and that the sign of this term is negative. In contrast, the corresponding coefficient is not significant in columns 3 and 6 for the non-ES industry group. Therefore, the EI-CAPE relation changes only for high emissions firms.

These results suggest that the implementation of the 2013 Regulation to disclose carbon emissions has a significant, albeit economically small, impact on the relationship between EI and the CAPE (expected equity returns) for firms in high emissions industry group. Specifically, for a firm with the average EI value (225.10, as shown in Table 1), the CAPE would be reduced by 0.68 (-0.003 × 225.1). Therefore, for an average firm, the CAPE would decrease from 19.1 to 18.42, resulting in the earnings yield (calculated as 1/CAPE) increasing from 5.24% to 5.43%, a rise of 19 basis points. This is an economically significant result, as it indicates a higher cost of external financing for firms with high EI values, thus influencing their capital allocation decisions. We interpret this result as an indication that, after the GHG emissions regulation come into force in 2013, investors have become more sensitive to firms' exposure to the climate risk. In this context, they are more inclined to exert financial pressure on companies with higher carbon intensity, demanding higher returns from these firms as compensation for their greater exposure to climate risk.

Overall, these results indicate that before 2013, markets didn't seem to prioritize carbon risks when making investment decisions. However, the adoption of the GHG emissions regulation in 2013 alters this trend. As access to emissions data improves and becomes easily accessible, investors typically show increased sensitivity to carbon risks and place more emphasis on a company's emissions intensity. In this context, investors tend to require higher returns from high EI firms, viewing these returns as compensation for climate transition risk. Since we do not find any evidence of investors differentiating between firms from within an industry, we conclude that these results are related to the social aspect of the NIT. Therefore, legitimacy concerns rather than efficiency considerations seem to be driving our results.

4.3. Further analysis and robustness tests

4.3.1. Autoregressive distributed lag (ARDL) regressions

While GMM is deemed suitable for coefficient estimation in dynamic panel data models due to its ability to deal effectively with endogeneity concerns, another prominent technique used for estimating long-run relationships in a single equation framework is the ARDL model.[5] The following specification was used to obtain ARDL estimates:

$$\begin{aligned}\Delta CAPE_{i,t} = {} & \gamma\,(CAPE_{i,t-1} + \beta_2 GHGeR + \beta_3 EI_{i,t} + \beta_4 GHGeR \times EI_{i,t} + \beta_5 LEV_{i,t} + \beta_6 Beta_{i,t} \\ & + \beta_7 Size_{i,t} + \beta_8 IAR_{i,t}) + (\beta_9 \Delta EI_{i,t} + \beta_{10} \Delta LEV_{i,t} + \beta_{11} \Delta Beta_{i,t} + \beta_{12} \Delta Size_{i,t} \\ & + \beta_{13} \Delta IAR_{i,t} + \alpha) + \boldsymbol{\varepsilon_{i.t}} \end{aligned} \tag{6}$$

As shown in Equation (6), the ARDL model estimates both short-run and long-run relationships between CAPE and the other covariates. The short run analysis employs annual changes, or first differences, in variables (denoted by Δ as the prefix), while the long-run estimates use level variables. The short-run regression includes

Table 6. ARDL estimates.

	CAPEe			CAPEr		
	(1) Full sample	(2) ES group	(3) Non-ES group	(4) Full sample	(5) ES group	(6) Non-ES group
ECT/Long Run						
GHGeR	2.972***	1.742*	3.669**	4.127***	3.210*	4.746***
	(2.64)	(1.86)	(2.38)	(3.45)	(1.68)	(2.92)
EI	0.003*	0.003**	0.005	0.004*	0.003**	0.006
	(1.83)	(2.03)	(1.46)	(1.71)	(1.98)	(1.49)
GHGeR × EI	−0.006**	−0.006**	−0.002	−0.006**	−0.006*	−0.003
	(−2.45)	(−1.97)	(−0.27)	(−2.36)	(−1.87)	(−0.39)
LEV	−0.008	−0.001	−0.008	−0.009	−0.007	−0.006
	(−0.65)	(−0.06)	(−0.54)	(−0.70)	(−0.28)	(−0.37)
Size	−4.032**	−4.952	−2.975	−4.572**	−5.592	−3.567
	(−2.10)	(−1.40)	(−1.34)	(−2.27)	(−1.50)	(−1.53)
Beta	−1.745	−6.198*	1.874	−2.081	−6.455*	1.269
	(−0.84)	(−1.76)	(0.73)	(−0.96)	(−1.75)	(0.47)
IAR	−2.625	−1.833	−0.581	−2.526	−1.681	−1.050
	(−0.63)	(−0.26)	(−0.11)	(−0.58)	(−0.22)	(−0.19)
Short Run						
ECT	−0.415***	−0.367***	−0.468***	−0.416***	−0.365***	−0.471***
	(−15.05)	(−9.58)	(−11.59)	(−15.23)	(−9.61)	(−11.75)
ΔEI	0.002	0.003*	−0.012*	0.002	0.003*	−0.013*
	(1.23)	(1.83)	(−1.89)	(1.16)	(1.81)	(−1.91)
ΔLEV	−0.013**	−0.013	−0.015**	−0.014**	−0.012	−0.016**
	(−2.56)	(−1.58)	(−2.19)	(−2.53)	(−1.38)	(−2.33)
ΔSize	3.479***	1.492	5.132***	3.999***	1.869	5.912***
	(2.91)	(0.85)	(2.98)	(3.18)	(1.02)	(3.24)
ΔBeta	−2.836***	−2.956**	−2.524*	−2.645***	−2.657*	−2.397*
	(−2.96)	(−2.06)	(−1.94)	(−2.63)	(−1.77)	(−1.75)
ΔIAR	−0.051	0.598	0.007	−0.021	0.468	0.393
	(−0.03)	(0.21)	(0.00)	(−0.01)	(0.15)	(0.14)
Intercept	45.193***	49.095*	38.087*	50.556***	54.197*	44.863*
	(2.61)	(1.70)	(1.69)	(2.78)	(1.80)	(1.89)
Observations	1,007	456	551	1,007	456	551
Number of firms	127	54	73	127	54	73

Notes: This table presents the estimates of ARDL model estimated using dynamic fixed effects estimator. The upper half of the table reports the long-run estimates/Error Correction Term (ECT) and the bottom half reports the short run estimates based on regressing the first difference of CAPE on explanatory variables shown in Equation (5). ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively.

the long run equation as an explanatory variable, commonly referred to as the error correction term (ECT), with γ as its coefficient. Given the mean-reverting nature of CAPE, a negative value for γ is expected.

To incorporate the introduction of the 2013 regulation in our analysis, we included the indicator variable GHGeR and its interaction with EI as explanatory variables in the long-run equation. To highlight this regulation's differential impact across polluting and non-polluting industries, we also report results obtained by splitting the full sample into ES and non-ES groups. For completeness, the regressions are performed on both, the earnings-based and revenue-based versions of CAPE.

The estimates for the ARDL model outlined in Equation (6) are presented in Table 6. As expected, the ECT obtains a negative coefficient in the short-run equation, suggesting that firms tend to revert towards their long-run financial performance after any short-run divergence. The high significance of the ECT term indicates that the variables in the long-run equation jointly have a significant impact on CAPE.

In the long-run regressions, the coefficients of GHGeR (within the ECT) suggest that the 2013 regulation has had a significant and persistent impact on CAPE. However, EI is significant only for firms in polluting industries, and its interaction with GHGeR is also significant for these industries. Specifically, for the ES group, emissions intensity is negatively associated with CAPE (positively associated with expected returns) following the introduction of the 2013 regulation. This finding is consistent with the results reported in Table 5. Overall, these results corroborate the findings obtained from the GMM regressions.

4.3.2. Instrumental variable (IV) regressions

We employ instrumental variable (IV) regressions to address endogeneity concerns arising from the relationship between lagged values of CAPE and EI. In the first stage of the two-stage least squares (2SLS) IV regression, we use the average annual EI at the industry level, denoted as Ind_Avg_EI, as an instrument for EI. Since a single instrument does not permit overidentification tests, we supplement Ind_Avg_EI with additional instruments derived from control variables using Lewbel's (2012) method. This approach allows for the identification of structural parameters in regression models with endogenous or mismeasured regressors, even in the absence of conventional instruments or repeated measurements. Following this method, we construct four additional instruments based on the control variables: leverage (Inst_{Lev}), size ($\text{Inst}_{\text{Size}}$), beta ($\text{Inst}_{\text{Beta}}$), and IAR ($\text{Inst}_{\text{IAR}}$). Two-way fixed effects regressions controlling for firm and time (year) fixed effects are used in estimation. The standard errors are clustered at industry-year level for robust estimation. Therefore, following equation is used to perform the first stage of the IV regression:

$$\begin{aligned} EI_{i,t} = {} & \alpha + \beta_1 Ind\_Avg\_EI_{i,t} + \beta_2 Inst_{Lev\,i,t} + \beta_3 Inst_{Beta\,i,t} + \beta_4 Inst_{Size\,i,t} + \beta_5 Inst_{IAR\,i,t} \\ & + \beta_6 LEV_{i,t} + \beta_7 Beta_{i,t} + \beta_8 Size_{i,t} + \beta_9 IAR_{i,t} + Firm_i + Year_t + \boldsymbol{\varepsilon_{i.t}} \end{aligned} \tag{7}$$

The second stage of the IV regression, following Equation (5), uses the predicted values of EI (denoted as pEI) from the first stage in place of the original EI values.[6] The second stage rgresThe results of these second-stage IV regressions, presented in Table 7, are qualitatively consistent with those in Table 5. Specifically, a negative and statistically significant interaction coefficient is obtained for the interaction between GHGeR indicator and pEI (denoted as GHGeR × pEI) in case of firms from polluting industries but not for firms from low environmental impact industries. These findings confirm that the 2013 regulation significantly increased the importance of environmental considerations in investors' decision-making for firms in environmentally sensitive industries.

Table 7 also presents three diagnostic tests that validate our instrumental variables approach: the Cragg-Donald Wald F statistic (testing for weak instruments), the Kleibergen-Paap rank LM statistic (testing for under-identification), and the Hansen J statistic (testing for overidentification). The table further reports the F-statistic for the joint significance of GHGeR, pEI, and their interaction term.

4.3.3. Difference-in-differences (DiD) analysis

To complement the analysis presented hitherto in the paper, we conduct DiD regressions testing differential impact of the 2013 regulation on polluting and non-polluting industries. This approach enables us to highlight the changes in investor response to GHG emissions specific to firms from polluting industries following the implementation of the 2013 regulation. Following El Hajjar et al. (2024), the equation used in DiD regressions is expressed mathematically as[7]:

$$\begin{aligned} CAPE_{i,t} = {} & \alpha + \beta_1 CAPE_{i,t-1} + \beta_2 CAPE_{i,t-2} + \beta_3 EI_{i,t} + \beta_4 GHGeR + \beta_5 ES_i \\ & + \beta_6 GHGeR \times EI_{i,t} + \beta_7 ES_i \times EI_{i,t} + \beta_8 GHGeR \times ES_i \times EI_{i,t} + \beta_9 LEV_{i,t} \\ & + \beta_{10} Beta_{i,t} + \beta_{11} Size_{i,t} + \beta_{12} IAR_{i,t} + Ind_i + Year_t + \boldsymbol{\varepsilon_{i.t}} \end{aligned} \tag{8}$$

Three-way interaction between EI, ES and GHGeR, denoted as GHGeR × ES × EI, is the key variable of interest in this regression. Its coefficient, β_8, represents the change in CAPE-EI relationship for firms from high-emissions industries following the implementation of the 2013 regulation. The coefficients of interactions of EI with GHGeR (β_6) and ES (β_7) are also of interest. Specifically, β_6 captures the change in CAPE-EI relation in response to the implementation of the 2013 regulation (GHGeR $= 1$) for firms belonging to low-emissions industries (ES $= 0$). Similarly, β_7 captures the average difference in the slope of EI on CAPE between high-emissions industries (ES $= 1$) and low-emissions industries (ES $= 0$), in pre-2013 period.

To address time-invariant unobserved heterogeneity and concerns about omitted variable bias, we control for industry and time (year) fixed effects in estimation. The standard errors are clustered at industry-year level for robust estimation. We also perform separate regressions to test that parallel-trends assumption, required for the application of DiD approach, holds in our sample. The results of these regressions are reported in Table A3 in the appendix.

Table 7. Instrumental variable regressions.

	CAPEe			CAPEr		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full sample	ES group	Non ES group	Full sample	ES group	Non ES group
$CAPEe_{t-1}$	0.903***	0.699***	0.668***			
	(16.25)	(7.57)	(8.98)			
$CAPEe_{t-2}$	−0.042	0.079	−0.036			
	(−0.78)	(0.84)	(−0.58)			
$CAPEr_{t-1}$				0.893***	0.701***	0.658***
				(16.05)	(7.63)	(9.11)
$CAPEr_{t-2}$				−0.032	0.082	−0.029
				(−0.60)	(0.89)	(−0.47)
GHGeR	1.771***	2.981**	−0.148	1.611**	2.698**	−0.524
	(2.62)	(2.35)	(−0.09)	(2.38)	(2.06)	(−0.31)
pEI	0.005**	0.005***	0.002	0.005**	0.006***	0.002
	(2.53)	(2.85)	(0.88)	(2.43)	(2.64)	(0.86)
GHGeR × pEI	−0.006**	−0.007***	−0.002	−0.006**	−0.008**	−0.003
	(−2.45)	(−2.97)	(−0.44)	(−2.18)	(−2.37)	(−0.46)
LEV	−0.000	−0.002	−0.007	−0.000	−0.002	−0.007
	(−0.07)	(−0.26)	(−1.31)	(−0.03)	(−0.32)	(−1.22)
Size	−0.735***	−2.697**	−0.077	−0.771***	−2.826**	−0.267
	(−5.91)	(−2.30)	(−0.07)	(−6.08)	(−2.34)	(−0.25)
Beta	−1.134*	−2.339**	−1.380**	−1.124*	−2.245*	−1.329**
	(−1.89)	(−2.09)	(−2.34)	(−1.80)	(−1.95)	(−2.36)
IAR	−0.063	−0.026	0.166	−0.073	−0.136	0.141
	(−0.08)	(−0.01)	(0.11)	(−0.09)	(−0.07)	(0.08)
Intercept	19.165***	60.929**	13.135	20.350***	64.443**	18.406
	(5.94)	(2.35)	(0.61)	(6.08)	(2.42)	(0.83)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,007	456	551	1,007	456	551
Number of Firms	127	54	73	127	54	73
F statistic	3.37**	3.03**	0.44	2.96**	3.29**	0.54
Diagnostic tests for instruments' validity:						
Kleibergen-Paap rank LM statistic for under-identification					23.82***	
Cragg-Donald Wald F statistic for weak identification					292.65	
Hansen J statistic for overidentification *p*-value					0.161	

Notes: This table presents results obtained using instrumental variable regressions. These regressions instrument EI using a combination of average annual industry EI with instruments derived from control variables using Lewbel (2012) method. GHGeR is an indicator variable that takes value 1 for year 2013 or later and 0 otherwise. ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively. T-statistics are given in parentheses. The F test statistic for the joint significance of GHGeR, EI and their interaction term for each regression is reported at the bottom of the table.

Table 8 presents the results of the DiD analysis. These findings are qualitatively similar to those reported earlier in Tables 5–7. The coefficient $\beta_6$is not statistically significant, suggesting that for low-emissions industries, the CAPE-EI relation did not significantly change in the post-2013 period. Likewise, the coefficient β_7 also is only weakly significant in two regressions, suggesting that there is no significant difference in the CAPE-EI relation between high and low-emissions industries before the implementation of the 2013 regulation.

In contrast, β_8 is negative and statistically significant in all specifications, which further confirms that for high-emissions industries, the CAPE-EI relation changed following the implementation of the 2013 regulation. We interpret this result as evidence that the 2013 regulation increased the importance of climate risk in investors' decision-making, leading to higher expected returns for firms in industries with greater GHG emissions, as they face higher exposure to climate risk.

5. Conclusion

In this article, we explore the relationship between emissions intensity (an indicator of climate risk exposure) and long term expected returns (as indicated by the CAPE ratio) for non-financial firms listed in the FTSE

Table 8. Difference-in-differences regressions.

	(1) CAPEe Coef./(t-stat)	(2) CAPEe Coef./(t-stat)	(3) CAPEr Coef./(t-stat)	(4) CAPEr Coef./(t-stat)
$CAPEe_{t-1}$	0.937***	0.899***		
	(18.13)	(16.21)		
$CAPEe_{t-2}$	−0.049	−0.045		
	(−0.94)	(−0.84)		
$CAPEr_{t-1}$			0.926***	0.888***
			(17.94)	(16.06)
$CAPEr_{t-2}$			−0.039	−0.035
			(−0.75)	(−0.66)
EI	−0.001	−0.001	−0.001	−0.001
	(−0.83)	(−0.91)	(−0.81)	(−0.90)
GHGeR	2.033**	2.017*	1.922*	1.849*
	(1.98)	(1.93)	(1.74)	(1.67)
ES	−0.657	−0.928**	−0.685	−0.961**
	(−1.60)	(−2.19)	(−1.56)	(−2.13)
GHGeR × EI	0.000	0.001	−0.000	0.001
	(0.01)	(0.43)	(−0.06)	(0.38)
ES × EI	0.002	0.003*	0.002	0.003*
	(1.38)	(1.83)	(1.35)	(1.80)
GHGeR × ES × EI	−0.001**	−0.002**	−0.001*	−0.002**
	(−1.97)	(−2.01)	(−1.86)	(−1.98)
LEV		−0.002		−0.002
		(−0.72)		(−0.67)
Size		−0.653***		−0.686***
		(−5.33)		(−5.49)
Beta		−1.202*		−1.193*
		(−1.97)		(−1.86)
IAR		−0.013		−0.022
		(−0.02)		(−0.03)
Intercept	3.654***	19.968***	4.062***	21.196***
	(3.41)	(6.33)	(3.48)	(6.48)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,007	1,007	1,007	1,007
Number of Firms	127	127	127	127
Adj. R-sq	0.811	0.818	0.812	0.819

Notes: This table presents regression results obtained using specification outlined in Equation (8). All regressions use two-way fixed effects regressions. EI is a continuous variable denoting firm-specific annual emissions intensity. ES is an indicator variable taking value 1 for polluting industries and 0 otherwise, whereas GHGeR is an indicator variable that takes value 1 for year 2013 or later and 0 otherwise. Standard errors clustered at industry-year level have been used for robust estimation. ***, ** and * represent statistical significance at 1% or better, 5% and 10% levels respectively. T-statistics are given in parentheses.

350 index. We track the changes in investor response to emissions data and its impact on expected returns as emissions disclosure transitions from a voluntary regime to a mandatory regime over the 2005–2019 period. Our focus is on studying the impact implementation of Strategic Report and Directors' Report Regulation 2013, has on emissions intensity – expected return nexus. Using GMM-estimated dynamic panel data models to analyse an unbalanced panel dataset containing 1007 firm-year observation drawn from 127 UK listed firms, our study makes several important contributions.

First, we contribute to the literature examining the link between GHG emissions and the CFP. While few studies have investigated the impact of ESG ratings of firms on their near-term financial performance, the long-term impact of emissions disclosure on financial performance has been rarely explored. We contribute to this stream of literature by revealing that there exists a statistically significant, but weak, association between corporate emissions intensity and long-term equity returns in the UK market. We discover that higher carbon intensity is linked to lower future long-term equity returns before emissions disclosure became mandatory in 2013 even after controlling for industry fixed effects. However, the statistical significance disappears when industry-year-adjusted emissions intensity is used for estimation. Additionally, we find no significant difference in EI-expected return relation between high and low emissions industries before 2013. This result complements the findings of prior studies (e.g. Aswani, Raghunandan, and Rajgopal 2024 and Bolton and Kacperczyk 2021) which find no significant association between emissions intensity and financial returns.

Second, we contribute to the literature examining the financial outcomes of mandatory CSR reporting. Based on the notion that mandatory reporting does not lead to substantive changes in business operations, few studies question the 'real world' impact of such policies (e.g. see Jackson et al. 2020). Our results point to the contrary as we observe a change in the sign of EI-expected return relation after the implementation of the 2013 regulation. This suggests that mandatory disclosure of emissions data has been instrumental in elevating climate-related concerns in investors' decision-making process leading them to demand compensation for bearing climate transition risk. Thus, mandatory disclosure can indeed influence significant stakeholders of firms, ultimately impacting their market value. This result complements the findings of Downar et al. (2021), which reports reduction in GHG emissions by UK listed firms without suffering any deterioration in their financial operating performance following the implementation of the 2013 regulation.

Third, our results provide evidence in favour of the social dimension of the NIT. We find that after the implementation of the 2013 regulation, the negative association between EI and expected returns turns positive only for high emissions industries. This heterogenous impact on expected returns for the high and low emissions industry groups suggests that investors distinguish between high and low emissions industries, but not across firms within an industry. As the 2013 regulation increased the amount and transparency of information available about firms' GHG emissions, investors are now more aware of the climate risks high emissions industries face. Therefore, this result concords with predictions of Pastor et al. (2021) who assert that green assets have relatively lower expected returns because investors enjoy holding them and because green assets are a hedge against climate risk. It also complements the findings of Haque and Ntim (2020) which finds that firms focus on process-oriented carbon reduction initiatives undertaken to enhance investors' perceptions.

Our research holds potential importance when considering the inclusion of carbon disclosure as an important aspect of nonfinancial disclosure. The adoption of the 2013 regulation has enriched the informational environment for investors, enabling more informed decision-making based on comprehensive insight into carbon emissions reduction performance of firms. It provides new insights for capital market participants, substantiating the premise that mandatory disclosure can help inform stakeholders about the environmental impact of businesses, specifically those associated with carbon emissions reductions. Such transparency not only benefits the investment community but also fosters corporate responsibility, potentially contributing to broader climate-related goals leading to more sustainable business practices. Moreover, these results provide critical evidence to policymakers, regulators and capital market authorities who have already established or are considering the implementation of compulsory GHG emission reporting.

Finally, our research is subject to some limitations and raises additional questions that further research could address in the future. Firstly, our study did not consider companies' Scope 3 emissions and the market response to carbon-related disclosure scores, both of which could be explored in future research. Secondly, using Scope 3 data will also facilitate inclusion of financial intermediaries into the analysis as bulk of their emissions fall within this category. Finally, our study focuses on UK listed firms, so future research could enhance the generalizability of results by incorporating firms from countries with varied economic, institutional, and cultural characteristics.

Notes

1. The Companies Act 2006 (Strategic Report and Directors' Report) Regulations 2013 (SI 2013/1970) (Strategic Report Regulations 2013) were introduced on 9 August 2013 and were implemented on 1 October 2013. The amendment inserted provisions into Schedule 7 of regulation 7, which deals with matters to be dealt with in directors' report of the Large and Medium-sized Companies and Groups (Accounts and Reports) Regulations 2008 (SI 2008/410).
2. Following definitions of scopes 1, 2 and 3 emissions are based on the GHG Protocol established by the World Resource Institute and World Business Council for Sustainable Development (WRI and WBCSD 2004). Scope 1: Direct GHG emissions from operations that are owned or controlled by the firm, including generation of electricity, heat and steam; physical and chemical processing; transportation of materials, products, waste and employees; fugitive emissions. Scope 2: Indirect

GHG emissions from the generation of purchased electricity, steam, and heating/cooling that is consumed in its owned and controlled operations. Scope 3: Other indirect GHG emissions from the upstream and downstream supply chain, including extraction, production, and transportation of purchased materials/fuels; use of sold products and services; operations of leased/franchised/outsourced assets.

3. Aswani et al. (2024) contend that such estimates are generated by database providers using deterministic functions that incorporate various firm-specific financial variables, including total assets and sales, leading to a high correlation between emissions and financial variables.
4. The ES group includes aerospace & defense; air freight & logistics; airlines; beverages; chemicals; commercial services & supplies; communications equipment; construction & engineering; construction materials; electric utilities; electrical equipment; electronic equipment, instruments & components; energy equipment & services; food & staples retailing; food products; household durables; household products; metals & mining; oil, gas & consumable fuels; paper & forest products; textiles, apparel & luxury goods; transportation infrastructure industries.
5. We thank the anonymous referee for suggesting the inclusion of this method in our analysis.
6. The results of the first stage regressions are reported in Table A2 in the Appendix.
7. We thank the anonymous referee for suggesting the specification shown in Equation (8).

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No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from Refinitiv. Restrictions apply to the availability of these data, which were used under license for this study.

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