# The Impact of Environment on Firm Performance: The Moderating role of Mandatory Energy Efficiency Scheme

## Abstract

This study examines the non-linear relationship between emissions and corporate financial performance (CFP), while assessing the moderating role of Environmental Regulatory Exposure (ERE). Using a balanced panel of 92 listed nonfinancial Indian firms from 2017 to 2022. The study employs quantile fixed-effects regression to capture variation across the performance distribution. The findings reveal an inverted U-shaped relationship, indicating that emissions initially enhance performance but becomes detrimental beyond a threshold. The results further show that firms do not respond uniformly to regulatory pressure. For lower-performing firms, regulatory exposure is associated with a higher emissions threshold, suggesting gradual adjustment and efficiency improvements. In contrast, for higher-performing firms, the threshold occurs earlier, indicating more stringent performance constraints. These findings highlight that regulatory pressure reshapes firm behaviour rather than uniformly reducing performance. The study contributes to the business literature by demonstrating that firms require differentiated strategies to manage emissions and sustain performance under regulatory environments.

**Keywords:** Greenhouse gas emissions; Financial performance; Quantile regression; Environmental regulation.

## 1. Introduction

Industrialisation has historically driven economic growth while simultaneously increasing emissions, leading to significant environmental degradation (Dasgupta & Roy, 2023; Grossman & Krueger, 1991). Consequently, this has intensified the debate on whether firms can balance environmental performance with financial outcomes. Prior research presents mixed evidence. Some studies suggest that environmental performance increases operational and compliance costs, thereby negatively affecting corporate financial performance (Le & Nguyen-Phung, 2024). In contrast, other studies argue that integrating sustainable practices can enhance financial outcomes through efficiency gains, innovation, and improved reputation (Fujii et al., 2012). These contrasting perspectives highlight that the relationship between emissions and CFP is complex and involves a trade-off between costs and benefits at the firm level (Trumpp & Guenther, 2015).

Firms operate within regulatory environments that influence how they manage emissions and allocate resources. This study does not directly compare firms across industries; rather, it examines whether the emissions–performance relationship differs under varying regulatory environments. This perspective aligns with prior research, which recognises that environmental–financial relationships are inherently heterogeneous and shaped by firm- and industry-specific conditions, and are therefore more appropriately analysed using moderation frameworks rather than direct cross-sectional comparisons (Dechezleprêtre & Sato, 2017; You et al., 2024). Environmental regulations are designed to encourage efficiency improvements and technological adaptation, thereby shaping firm behaviour (Dechezleprêtre & Sato, 2017). However, the impact of regulatory pressure is unlikely to be uniform, as firms differ in their capacity to absorb compliance costs, adopt cleaner technologies, and optimise operational processes. Consequently, the relationship between emissions and financial performance is expected to vary across firms depending on their performance levels and strategic responses.

Market-based regulatory instruments provide flexibility in achieving environmental targets while allowing firms to maintain operational performance. In this context, the Perform, Achieve, and Trade (PAT) scheme focuses on improving energy efficiency by setting intensity-based targets (Yu et al., 2022). Such mechanisms enable firms to improve environmental performance through efficiency gains while continuing to pursue growth objectives (Μακρίδου et al., 2019).

While prior studies have examined the relationship between environmental regulation and firm performance, evidence from emerging economies remains limited (Gerged et al., 2020). This is particularly relevant in the context of India, where firms operate under increasing environmental pressures alongside strong growth dynamics (Raza et al., 2024). Further, this study also advances theoretical understanding by applying the Environmental Kuznets Curve (EKC) and the Porter Hypothesis. The EKC predicts a non-linear relationship between environmental degradation and economic outcomes, while the Porter Hypothesis emphasises the efficiency-enhancing potential of well-designed regulation.

Moreover, most studies have used linear models, whereas our study uses a non-linear model. Prior evidence suggests that the impact of emissions on CFP is not monotonic (Trumpp & Guenther, 2015). A non-linear model accounts for the effect of emissions on CFP by capturing changes across different emission levels. A linear specification would impose a uniform effect by averaging these opposing effects and thereby failing to capture the threshold levels. To address this limitation, this study employs panel quantile regression (PQR), which allows for the estimation of distributional heterogeneity and the identification of turning points across firms. Accordingly, this study examines the non-linear relationship between GhG emissions and corporate financial performance while assessing the moderating role of ERE. Using a balanced panel of 92 Indian-listed firms over the period 2017–2022, the analysis captures variation in the performance distribution and distinguishes between firms exposed to regulatory mechanisms and those unexposed to the regulatory framework.

The findings of our study reveal an inverted U-shaped relationship: moderate emissions initially enhance CFP, but emissions above a threshold decline CFP. More importantly, regulatory exposure alters this relationship in a heterogeneous manner. The findings suggest that lower-performing firms can extend the range of emissions that do not adversely affect firm performance. This can be attributed to gradual adjustment mechanisms, whereby regulatory pressure encourages improvements in energy efficiency and the adoption of cleaner production processes (Oak & Bansal, 2022).

In contrast, higher-performing firms experience earlier performance trade-offs under regulatory exposure. As these firms are already operating closer to their efficiency frontiers, the scope for further efficiency gains is relatively limited. Moreover, additional regulatory requirements impose binding constraints, leading to rising compliance costs and diminishing marginal returns from emission-intensive activities (Gerged et al., 2020). This implies that for high-performing firms, regulatory pressure accelerates the point at which emissions begin to adversely affect performance, reflecting tighter operational and financial constraints. These findings suggest that regulatory pressure reshapes firm behaviour rather than exerting uniform effects on performance (Chauhan & Thangavel, 2025).

This study contributes to the business literature in three ways. First, it provides evidence of a non-linear relationship between emissions and performance, highlighting the importance of threshold effects. Second, it demonstrates that regulatory exposure influences firm behaviour in a heterogeneous manner across the performance distribution. Third, it offers managerial implications by showing that firms require differentiated strategies to manage emissions and sustain performance under regulatory environments, particularly in emerging economies.

## 2. Literature Review and Hypothesis Development

### 2.1 Theoretical Foundations

The most commonly used theories in the debate over the CFP and GhG nexus are stakeholder theory, signalling theory, and agency theory. On the one hand, signalling theory and stakeholder theory largely support a positive link between environmental disclosure and financial outcomes. For instance, signalling theory posits that transparent environmental practices, such as disclosing a firm's carbon footprint, can convey a firm's commitment to sustainability, attract socially responsible investors, and improve corporate reputation (Choudhary et al., 2018). Similarly, stakeholder theory (Donaldson & Preston, 1995) suggests that addressing the concerns of various stakeholders, including environmental groups, can enhance legitimacy and ultimately lead to superior financial performance. On the other hand, agency theory suggests that managers might prioritise personal gains over environmental investments that do not offer immediate financial benefits, potentially leading to a negative relationship between environmental performance and financial outcomes (Bodhanwala & Bodhanwala, 2018).

This divergence underscores the multifaceted nature of the relationship between GhG and CFP, highlighting the imperative for more nuanced analytical frameworks. To reconcile this complexity, the present study adopts a curvilinear approach, acknowledging that the nexus between environmental performance and financial outcomes is nonlinear (Broadstock et al., 2020; Gerged et al., 2020; Le & Nguyen-Phung, 2024). Grounded in two seminal theoretical frameworks, the Environmental Kuznets Curve (EKC)(Nielsen & Alderson, 1997) and Porter's Hypothesis (Porter, 1991; Porter & Linde, 1995).

The Environmental Kuznets Curve (EKC) hypothesis posits an inverted U-shaped relationship between environmental degradation and economic development, originally inspired by Simon

Kuznets' work on income inequality. The EKC framework, extensively developed and empirically validated in environmental economics, suggests that in the initial stages of economic growth, environmental degradation intensifies due to increased industrialisation and weak environmental governance (Grossman & Krueger, 1991). But, as income per capita rises and economies mature, there is a growing societal preference for environmental quality, accompanied by stronger regulations. Therefore, this evolution leads to a turning point beyond which environmental impact declines despite continued economic growth, reflecting enhanced environmental efficiency and sustainability.

This nonlinearity captures the trade-offs firms face between profitability and environmental responsibility (Trumpp & Guenther, 2015; Zheng et al., 2021). While the EKC elucidates the trajectory of pollution relative to economic growth, it does not inherently address the mechanisms by which firms manage the cost of environmental regulation. Therefore, we use Porter's Hypothesis that offers critical theoretical insights. Michael Porter (1991) argued that stringent yet flexible environmental regulations could stimulate innovation that offsets compliance costs and enhances firm's competitiveness (Porter, 1991). The "innovation offset" effect posits that environmental regulation is not purely a financial burden but can also act as a catalyst for technological improvements and efficiency gains, ultimately improving both environmental and economic performance (Porter & Linde, 1995).

In the context of India's ERE scheme, Porter's Hypothesis is particularly relevant for a market-based regulatory mechanism employing output-based energy intensity targets. By introducing flexibility and tradability, the ERE incentivises firms to invest in cleaner technologies and innovate while mitigating upfront compliance costs. Together, the EKC and Porter's Hypothesis provide a robust theoretical framework for interpreting the empirical nonlinear GHG-CFP dynamics observed across firm performance quantiles (Trumpp & Guenther, 2015). The EKC explains the fundamental inverted U-shaped GhG-CFP relationship, while Porter's

Hypothesis clarifies how flexible, innovation-friendly regulation like ERE modulates this relationship by enhancing firms' capacity to absorb regulatory costs and maintain financial viability amid environmental constraints.

### 2.2 Hypothesis Development

Prior studies across developed and emerging economies examining the relationship between GhG emissions and CFP provide mixed evidence. Some studies report a positive association, attributing improved financial performance to efficiency gains, innovation, and enhanced reputation (Yadav et al., 2015). For instance, Fujii et al. (2013) find that improvements in environmental performance enhance economic outcomes through energy efficiency. Similarly, Lee et al. (2015) document a short-term positive impact on financial performance following reductions in emissions. Evidence from European firms from 2005 to 2016 further suggests that improvements in environmental performance are associated with higher profitability (Tzouvanas et al., 2019). This viewpoint is similar to research on Japanese firms, indicating that lower emissions increase firm profitability (Iwata & Okada, 2011).

In contrast, other studies demonstrate a negative association, attributed to increased costs, as contested by (Le & Nguyen-Phung, 2024). Similarly, research by Delmas et al. (2015) was conducted on US firms, which found that a reduction in GhG emission performance reduces ROA in the short term. Such conflicting findings suggest that the emissions–performance relationship is complex and cannot be adequately explained using a linear framework.

Accordingly, a growing body of literature highlights nonlinear dynamics in the emissions–performance relationship (Kimbara, 2010; Misani & Pogutz, 2014; Trumpp & Guenther, 2015). For instance, Kimbara (2010) documents an inverted U-shaped relationship between emissions and return on assets (ROA), indicating that emissions initially contribute to higher profitability but become detrimental beyond a threshold level. This pattern reflects the trade-off between production-related gains at lower emission levels and rising regulatory, operational, and reputational costs at higher levels. This relationship is consistent with the Environmental Kuznets Curve (EKC) framework, which predicts that environmental degradation initially increases with economic activity but declines beyond a certain threshold. Applying this framework at the firm level suggests that moderate emissions may enhance financial performance, while excessive emissions reduce performance due to inefficiencies and regulatory penalties (Clarkson et al., 2010; Linn, 2009).

Therefore, based on the EKC theory and prior empirical evidence, the study hypothesises the following:

**Hypothesis 1: The relationship between GhG and CFP is non-linear, following an inverted U-shape relationship.**

Emission trading schemes and their impact on financial performance have been widely debated in the literature, particularly in the context of environmental regulations, such as command-and-control mechanisms and market-based energy-efficiency schemes (Li et al., 2017). Porter and van der Linde (1995) propose that well-designed environmental regulations can create a “win–win” outcome by encouraging firms to reduce emissions while improving efficiency and profitability. This perspective is supported by subsequent studies that highlight the role of energy-efficiency improvements in enhancing firm performance (Makridou et al., 2019; Zheng et al., 2021). These studies suggest that reductions in energy consumption lower operational costs, thereby improving profitability and financial performance.

However, the impact of environmental regulation is not uniformly positive. Some studies emphasise that regulatory compliance imposes additional costs and constraints on firms, particularly when emission limits are binding. For instance, Clarkson et al. (2010) and Linn (2009) show that pollution levels and emission constraints are associated with lower market value, as firms incur penalties and increased compliance costs. Evidence from cap-and-trade systems, such as the EU ETS and NOx trading programs, further indicates that firms may experience short-term reductions in profitability if they fail to adjust their environmental practices effectively.

In this context, market-based mechanisms such as the Perform, Achieve, and Trade (PAT) scheme offer a more flexible regulatory framework by allowing firms to achieve energy-efficiency targets through gradual adjustments. This flexibility enables firms to sustain operational performance in the short run while investing in efficiency improvements that enhance long-term profitability. As firms adopt energy-efficient technologies and optimise resource utilisation, they can reduce costs, mitigate risks associated with energy price fluctuations, and improve overall financial performance (Çoban & Topçu, 2013; Zhang et al., 2016).

These findings suggest that environmental regulation does not directly determine financial performance; rather, it influences how firms respond to emissions and operational challenges. Consequently, regulatory exposure is expected to modify the relationship between emissions and corporate financial performance, rather than exerting a uniform effect across firms.

**Hypothesis 2: ERE moderates the relationship between GhG emissions and CFP.**

Traditional empirical models often assume that the relationship between environmental performance and corporate financial performance is homogeneous across firms. However, firms differ significantly in their operational efficiency, resource endowments, and ability to respond to environmental and regulatory pressures. As a result, the impact of emissions on financial performance is unlikely to be uniform across the distribution of performance.

Prior literature highlights that the environmental–financial performance relationship is inherently heterogeneous, with firm responses varying depending on their capabilities, performance levels, and strategic positioning (Gerged et al., 2020; Trumpp & Guenther, 2015).

Lower-performing firms often have greater scope for efficiency improvements and operational adjustments, whereas higher-performing firms tend to operate closer to their efficiency frontiers, making them more sensitive to regulatory constraints and diminishing returns.

In the presence of environmental regulatory exposure, this heterogeneity becomes more pronounced. Regulatory mechanisms may allow lower-performing firms to gradually adapt through efficiency improvements and technological adoption, thereby delaying the adverse effects of emissions on performance. In contrast, higher-performing firms may experience earlier trade-offs, as additional regulatory requirements impose binding constraints and limit further efficiency gains. This argument is consistent with the Porter Hypothesis, which suggests that the benefits of regulation depend on firm-specific capabilities and the scope for innovation (Porter & Linde, 1995), as well as with evidence that regulatory impacts vary across firms and industries (Dechezleprêtre & Sato, 2017).

Accordingly, the moderating effect of environmental regulatory exposure is expected to vary across the distribution of performance.

**Hypothesis 3: The moderating effect of ERE on the relationship between greenhouse gas emissions and corporate financial performance varies across the performance distribution.**

Insert Table A.1

## 3. Data and Methodology

### 3.1 Sample and Data Sources

The study is based on a balanced panel dataset of 92 Indian listed companies covering the period from 2017 to 2022. Out of the 92 firms in the sample, 21 are designated consumers (DC firms) under the PAT scheme, while the remaining firms are non-DC. Although the distribution is uneven, it reflects the sector-specific nature of the PAT scheme and provides sufficient variation to identify the moderating role of regulatory exposure. Firm-level financial and market data were obtained from Bloomberg, while GhG emission information was sourced from the Bloomberg ESG database, which collates disclosures from company's sustainability reports and CDP filings. To ensure data consistency, only firms with complete annual disclosure of GhG emissions for the full period were retained, thereby providing a balanced dataset suitable for fixed-effects estimation.

The selection of the period 2017 to 2022 is guided by the regulatory trajectory of the Perform, Achieve and Trade (PAT) scheme in India. This study focuses on firms included in PAT Cycle III (2017–2020). Earlier cycles were not considered for two reasons. First, Cycle I (2012–2015) was in pilot phase with inconsistent disclosure and transitional compliance mechanisms, making it unsuitable for systematic firm-level analysis. Second, although Cycle II (2016–2019) expanded sectoral coverage, but firm-level GhG disclosures during this period remained fragmented and inconsistent in Bloomberg ESG data. Moreover, many firms were still in the process of technological and operational adjustments, making it difficult to disentangle compliance costs from efficiency gains. In contrast, Cycle III (2017–2020) represents a more mature phase of the scheme, characterized by stricter targets, broader sectoral inclusion, and more standardized GhG reporting.

Thus, the selection of this cycle reflects both data availability and the regulatory maturity of PAT scheme, ensuring that the analysis captures firms' responses during a phase when efficiency improvements and financial implications are more reliably. The sample size is constrained by disclosure availability, this pattern is consistent with international evidence, where GhG reporting is concentrated among large, visible firms (Lewandowski, 2017; Broadstock et al., 2017). Accordingly, the dataset is well suited to examine the curvilinear relationship between GhG emissions and CFP in the Indian context.

### 3.2 Variable Measurement

### 3.2.1 Firm Performance

The dependent variable in this study is firm financial performance**.** We employ Return on Assets (ROA) as the primary measure, defined as net income divided by total assets**.** ROA reflects the efficiency with which a firm utilizes its assets to generate profits and has been widely used in the literature examining the environmental–financial nexus (Clarkson et al., 2010). As an accounting-based indicator, ROA captures the operating performance of firms, making it suitable for evaluating whether the benefits of emissions reduction and energy efficiency are translated into improved profitability. The equation is denoted below:

$$\boldsymbol{ROA = \frac{Net\ Income}{Total\ Assets}} \quad \textbf{...(1)}$$

Further, as a robustness check, we also include Return on Equity (ROE)**,** calculated as net income divided by shareholders' equity. ROE represents returns delivered to equity investors and provides a complementary shareholder-oriented perspective on performance. While ROA focuses on asset utilization, ROE is sensitive to financial structure and leverage decisions, thereby offering a broader validation of the findings. The formulae for computation are denoted below:

$$\boldsymbol{ROE = \frac{Net\ Income}{Shareholders\ Equity}} \quad \textbf{...(2)}$$

The inclusion of both measures is theoretically motivated. On the one hand, improved environmental efficiency and lower emissions may reduce operating costs and enhance reputation, thus positively influencing profitability. On the other hand, compliance and abatement investments may initially reduce returns, particularly in capital-intensive firms. Therefore, using both ROA and ROE allows for a comprehensive evaluation of this trade-off, ensuring a more rigorous assessment of the curvilinear impact of GhG emissions on corporate financial outcomes.

### 3.2.2 GhG Emissions

The independent variable in this study is greenhouse gas (GhG) emissions, encompassing both Scope 1 emissions, which arise directly from firm-owned or controlled operations, and Scope 2 emissions, which result from the consumption of purchased electricity, heat, or steam. Firm-level data are sourced from the Bloomberg ESG database, which standardizes information disclosed in corporate sustainability reports, CDP submissions, and other verified channels.

Given the highly skewed distribution of raw emissions across firms, we employ the natural logarithm of total GhG emissions (LnGhG) as the main explanatory variable. To examine potential non-linearities in the emissions–performance nexus, we further include the squared term of Ln GHG, thereby allowing the estimation of curvilinear effects. This specification enables the testing of an inverted U-shaped relationship, whereby moderate increases in emissions may initially correspond with financial gains due to scale economies, but beyond a threshold, higher emissions are expected to impose regulatory, reputational, and efficiency costs. The adoption of both linear and quadratic terms follows prior empirical work on the environmental–financial interface (Trumpp and Guenther, 2017; Broadstock et al., 2017).

### 3.2.3 Control Variables

We include several firm-level controls to account for heterogeneity in financial outcomes. Firm size is proxied by the logarithm of market capitalization, reflecting scale and investor visibility (Broadstock et al., 2017). Leverage, measured as total debt to total assets, captures capital structure effects (Fujii et al., 2013). Market-to-book value (MTBV) is included as a proxy for growth opportunities (Broadstock et al., 2017), while asset turnover (sales-to-assets) controls for operational efficiency. To separate the effect of emissions from broader sustainability practices, we control for firms' ESG scores. Finally, firms age and sales growth are added to capture maturity and growth dynamics (Trumpp & Guenther, 2015; Lewandowski, 2017). These control variables ensure a robust specification that accounts for size, structure, efficiency, growth, and sustainability orientation when estimating the emissions–CFP relationship.

### 3.2.4 Moderating Variable: Environment Regulatory Exposure

The moderating role of environmental regulatory exposure is examined using a binary indicator derived from India's Perform, Achieve, and Trade (PAT) scheme, a market-based regulatory framework designed to promote energy efficiency. The variable PAT takes the value 1 for designated consumers (DC firms) covered under PAT Cycle III (2017–2020) and 0 otherwise. This classification captures variation in the intensity of regulatory exposure rather than policy eligibility, as non-DC firms, although not directly regulated, operate within the same broader economic and institutional environment.

The PAT scheme, administered by the Bureau of Energy Efficiency (BEE), assigns energy efficiency targets to DC firms and enables trading of surplus savings through Energy Saving Certificates (ESCerts). The inclusion of this variable is grounded in the Porter Hypothesis, which posits that well-designed environmental regulation can enhance firm efficiency and innovation (Porter & van der Linde, 1995). Consistent with prior literature, environmental regulation is treated as a contextual factor that generates heterogeneous firm responses rather than requiring direct comparability across firms (Dechezleprêtre & Sato, 2017; Trumpp & Guenther, 2015).

To capture the moderating effect, an interaction term (Ln(GhG) × ERE) is included, allowing the assessment of whether the marginal impact of emissions on corporate financial performance differs across firms facing varying levels of regulatory pressure. In this framework, the coefficient on the interaction term reflects how regulatory exposure modifies the emissions–performance relationship, rather than directly comparing firm outcomes.

While regulatory exposure under the PAT scheme is sector-specific, potential structural differences are addressed through the inclusion of industry fixed effects and firm-level controls. Accordingly, the analysis focuses on differences in marginal effects rather than cross-sectional comparisons across firms. A limitation of this approach is that regulatory exposure is not randomly assigned; therefore, the findings should be interpreted as conditional relationships rather than causal effects.

Insert Table A.2

### 3.3 Empirical Methodology

We empirically evaluate the relationship between firm's financial performance and greenhouse gas (GhG) emission using the Panel Quantile Regression (PQR) analysis, while allowing for potential non-linearities. The baseline model is without the ERE framework and can be expressed as:

$$\boldsymbol{FP_{it} = \beta_0 + \beta_1 \, ln(GhG)_{it} + \beta_2 \, [ln(GhG)_{it}]^2 + \gamma X_{it} + \varepsilon_{it}} \quad \textbf{..(3)}$$

Where, $FP_{it}$ denotes the financial performance of firm $i$ in year $t$ (proxied by ROA, and alternatively ROE for robustness). $\ln(GhG)_{it}$ represents the natural logarithm of Scope 1 and 2 GhG emissions, while $[\ln(GhG))_{it}]^2$ captures non-linear effects. $X_{it}$ is a vector of control variables (firm size, leverage, MTBV, asset turnover, ESG score, firm age, and sales growth) and $\varepsilon_{it}$ is the idiosyncratic error term.

Further, we extend the baseline equation by adding the ERE variable to examine the moderating effect of the scheme, we extend the specification as follows:

$$FP_{it} = \beta_0 + \ \beta_1 \, ln(GhG)_{it} + \beta_2 \, [ln(GhG)_{it}]^2 + \delta_1 ERE_{it} + \delta_2 [ln(GhG)_{it} \times ERE_{it}] + \gamma X_{it} + \varepsilon_{it} \qquad ..(4)$$

Here, $ERE_{it}$ is a binary variable equal to 1 if firm *i* is covered under PAT Cycle III, and 0 otherwise. The interaction term $\ln(GhG)_{it} \times ERE_{it}$ captures whether the relationship between emissions and performance differs for PAT compliant firms.

The previous literature examining the link between environmental performance and CFP has relied on conventional linear estimators such as ordinary least squares (OLS), Heckman instrumental variables (IV), or the generalized method of moments (GMM) (Le & Nguyen-Phung, 2024). These approaches estimate the conditional mean of the dependent variable given the regressors (Wooldridge, 2010[1]; Gerged et al., 2020) expressed as:

$$E(FP_{it} \, / X_{it}) = X'_{it}\beta, \qquad ..(5)$$

The traditional OLS method is based on a fundamental assumption that the error term is normally distributed (Wooldridge, 2010; Gerged et al., 2020)

$$\varepsilon \mid X \sim N \, (0, \sigma^2 I_n) \; ...(6)$$

Although essential, the model has drawbacks. For instance, the mean regression models provide only a partial view of the relationship, potentially overlooking heterogeneous effects across the performance distribution. For example, the impact of GhG emissions may differ substantially for low-performing and high-performing firms. Therefore, to capture this heterogeneity, Koenker & Bassett, 1978 introduced quantile regression (QR), which estimates

[1] Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.

conditional quantiles rather than conditional means. Unlike OLS, quantile regression is semiparametric, does not impose distributional assumptions on error terms, and is more robust to outliers (Baum, 2013[2]). This allows researchers to investigate how explanatory variables influence different points of the outcome distribution (e.g., 25th, 50th, 75th percentiles of firm performance).

Additionally, applying quantile regression to panel data presents further complexity. As traditional methods use additive fixed effects, which leads to bias because of incidental parameter issues when the time dimension is short. (Gerged et al., 2020). However, Canay (2011) addressed this by incorporating fixed effects in quantile regression, but challenges still remain when estimating a large number of individual effects. Therefore, to resolve this issue, Powell (2022) proposed a quantile regression for panel data (QRPD) with non-additive fixed effects**,** which remains consistent even with small *T*. The general model is expressed as:

$$(\boldsymbol{FP_{it}}) = \boldsymbol{D'_{i,t}\beta_{\tau}} + \boldsymbol{U_{i,t}}, \ldots \textit{(7)}$$

where $FP_{it}$ represents financial performance (ROA or ROE), $D'_{i,t}$ is the set of independent variables (GhG emissions, squared emissions, ERE, interaction terms, and controls), $\beta_{\tau}$ denotes the coefficient vector at quantile $\tau$, and $U_{i,t}$ is the error term incorporating both fixed and time-varying components.

Whereas, for the $\tau$-th quantile, the conditional restriction is:

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[2] Baum, C.F. (2013)." Quantile regression" (accessed April 22, 2029)http://fmwww.bc.edu/ec-c/s2013/823/EC823.S2013.nn04.slides.pdf

$$\boldsymbol{P\left( (FP_{it}) \leq D'_{i,t}\beta_\tau \mid D_{i,t} \right) = \tau.} \dots \textit{(8)}$$

This means that the conditional probability of firm performance falling below the estimated quantile function equals $\tau$ for any value of $\mathrm{D}_{i,t}$. Powell's estimator also satisfies an unconditional restriction:

$$\boldsymbol{D_{i,t}i = P\left( (FP_{it}) \leq D'_{i,t}\beta_\tau \mid D_{i,t} \right) = P\left( (FP_{it}) \leq D'_{i,t}\beta_\tau \mid D_{i,t} \right) = \tau.} \dots \textit{(9)}$$

where $\mathrm{D}_{i,t} = (D_{i\,,} \ldots, D_{i,t})_{\,,}$ is the sequence of covariates across time for firm *i*. This framework ensures that quantile restrictions hold both conditionally and unconditionally across the panel, allowing for consistent and interpretable estimates of the emissions–performance relationship in the presence of firm-level heterogeneity.

Additionally, we also calculate the turning point at which the financial performance begins to decline. This threshold analysis allows for a nuanced understanding of the non-linear relationship between GhG emissions and CFP, particularly highlighting the differential impact on firms within the environment regulatory exposure compared to environment regulatory non-exposure firms.

For environment regulatory non-exposure firms, the marginal effect of emissions on firm performance in the quadratic regression from Equation 3 given is:

$$\boldsymbol{\frac{\delta\, FP_{it}}{\delta\, ln(GhG)_{it}} = \beta_1\, ln(GhG)_{it} + \beta_2\, [ln(GhG)_{it}]^2} \dots \textit{(10)}$$

For environment regulatory non-exposure firms, the turning point occurs when the derivative is set to zero:

$$\boldsymbol{ln(GhG)^{*}_{Non-ERE} = -\frac{\beta_1}{2\beta_2}} \quad \textbf{\textit{Without Environment framework (Regulation=0) ...(11)}}$$

For environment regulatory exposure, the present regression includes the interaction term $\delta_2[\ln(GhG)_{it} \times ERE_{it}]$. Hence, the marginal effect from Equation 4 becomes:

$$\boldsymbol{\frac{\delta FP_{it}}{\delta \, ln(GhG)_{it}} = \beta_1 \, ln(GhG)_{it} + \delta_2[ln(GhG)_{it} \times ERE_{it}] + \beta_2 \, [ln(GhG)_{it}]^2} \textbf{\textit{...(12)}}$$

Setting this equal to zero gives the turning point for ERE firms:

$$\mathbf{ln(GhG)^{**}_{ERE} = -\frac{(\beta_1 + \delta_2)}{2\beta_2}} \quad \textbf{With Environment framework (Regulation=1) ... (13)}$$

Here, $GhG^{*}$ $and$ $GhG^{**}$ indicates the turning point.

## 4. Empirical Results and Discussion

### 4.1 Descriptive Statistics and Correlation Matrix

Table 1 presents the descriptive statistics of the variables employed in the analysis. The mean ROA and ROE are 8.83% and 15.83%, respectively, with wide variation, reflecting heterogeneity in firm profitability. The average value of Ln(GHG) is 2.58, with substantial dispersion (SD. 1.13), while the squared term indicates sufficient variation to test for non-linearity. The mean value of ERE is 0.23, indicating that approximately 23% of the sample firms are designated consumers (DC firms) under the PAT scheme, with the remaining firms classified as non-DC.

Among control variables, total asset turnover averages 0.86, indicating moderate efficiency in asset use, the mean Size of 5.51 indicates variation in firm scale, while Age shows relatively low dispersion, suggesting a fairly mature sample of firms. Sales Growth (SG) exhibits high variability, indicating differences in firm expansion dynamics. Financial leverage (LEV) has a mean of 21.74, with a wide range, suggesting differences in capital structure and financial risk across firms. MTBV also shows significant dispersion, reflecting heterogeneity in growth opportunities and market valuation. While the mean ESG score of 50.97 suggests mid-level sustainability engagement. Overall, the statistics reveal considerable dispersion across firms, justifying the use of a distributional approach to capture heterogeneous effects in the emissions–performance relationship.

Table 2 presents the correlation matrix. ROA and ROE are highly correlated (0.82), confirming their close alignment as profitability measures. Ln(GhG) shows a negative association with profitability. The positive correlation between ERE and Ln(GhG) at 0.599 reflects the sector-specific targeting of high-emission firms under the ERE scheme. Firm size correlates positively with both profitability and emissions, whereas leverage is negatively related to performance. Growth proxies (MTBV) and asset turnover are positively associated with profitability, while ESG aligns more strongly with firm size than with financial outcomes. Importantly, the coefficients remain moderate, suggesting that multicollinearity is not a concern for subsequent regression.

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Insert Table 1

Insert Table 2

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## 4.2 Main analysis

### 4.2.1 GhG- CFP Curvilinear Relationship

The empirical findings from Table 3 provide evidence of a non-linear relationship between GhG emissions and CFP, measured using RoA. The findings indicate that the coefficient of Ln(GhG) remains positive and statistically significant, while the squared term is consistently negative and significant, thereby confirming the presence of an inverted U-shaped relationship (Trumpp & Guenther, 2015) and supporting hypothesis 1. This pattern is consistent with the Environmental Kuznets Curve (EKC) hypothesis, suggesting that at lower levels, increases in emissions are associated with improved CFP due to economies of scale and production expansion (Nielsen & Alderson, 1997). However, beyond a critical threshold, further increases in emissions lead to declining profitability, reflecting rising compliance costs, regulatory pressures, and reputational risks (Gerged et al., 2020).

The estimated turning points vary across quantiles, indicating that the threshold at which emissions begin to adversely affect performance differs across firms. Firms in the lower quantiles reach the turning point at relatively higher emission levels, suggesting that low-performing firms continue to derive benefits from scale expansion for a longer period before facing the emissions–performance trade-off. This pattern can be partially explained by regulatory-induced innovation. Prior evidence from the EU Emissions Trading System (EU ETS) shows that regulated firms significantly increase innovation in low-carbon technologies. Such innovation may allow firms, particularly those operating below the efficiency frontier, to offset the costs of emissions through technological improvements, thereby delaying the onset of negative financial effects. These findings align with prior studies such as Broadstock et al. (2017), Misani and Pogutz (2014), and Lewandowski (2017), which document similar non-linear dynamics.

#### 4.2.2 Moderating the Role of Environment Regulation Exposure.

Additionally, Table 4 examines how ERE moderates the relationship between GhG and CFP. The interaction term (*Ln(GhG)* × *ERE*) is positive and significant at lower quantiles (e.g., 0.10–

0.70) and weakens toward the higher quantiles, turning negative at the 0.95 quantile. This indicates that ERE changes the marginal effect of emissions and shifts the turning point of the relationship, thus confirming hypothesis 2.

Consistent with this, the estimated turning points under higher regulatory exposure (*ERE = 1*) are above those under non-exposure (*ERE = 0*) at lower quantiles. For instance, at the 0.10 quantile, the turning point increases from 2.63 to 5.16, and at the 0.20 quantile from 2.29 to 3.99 (thousand metric tons). This upward shift implies that, for lower-performing firms, regulatory exposure extends the range of performance over which emissions are positively associated.

In contrast, for higher-performing firms, this pattern reverses. At the 0.95 quantile, the interaction term is negative and significant. Whereas the turning point under environmental exposure (2.47) is lower than that under non-exposure (3.37). This indicates that, for higher-performing firms, ERE shifts the trade-off forward, leading to an earlier decline in performance.

The differential timing of the turning point can be explained using the marginal abatement cost (MAC) and expected marginal penalty (EMP) framework (Prasad & Mishra, 2016). Higher-performing firms operate closer to the efficient frontier, where gains from scale, process optimisation, and capacity utilisation have largely been exhausted. At this stage, additional emissions generate limited incremental output while increasing costs related to inefficiencies, compliance, and environmental management. Consequently, both marginal abatement costs and expected penalties rise more rapidly, leading to an earlier intersection of costs and benefits and, therefore, an earlier turning point(Prasad & Mishra, 2016).

In contrast, lower-performing firms are characterised by greater operational slack, including underutilised capacity and inefficiencies. Under such conditions, emissions remain associated with incremental improvements in production and cost absorption over a wider range. As a result, the marginal benefits of emissions persist longer relative to associated costs, delaying the onset of the trade-off and resulting in a higher turning point. This suggests that regulatory exposure enables a gradual adjustment process for less efficient firms, while imposing tighter constraints on firms already operating at high efficiency levels, thus supporting hypothesis 3. This occurs because the PAT scheme introduces efficiency targets and compliance incentives, encouraging firms to adopt energy-efficient practices and technological improvements. For lower-performing firms, this facilitates a gradual adjustment process, allowing them to sustain gains from emissions over a longer range. In contrast, higher-performing firms, which operate closer to their efficiency frontier, face higher marginal abatement costs and regulatory pressures, leading to an earlier decline in performance.

Thus, ERE does not directly improve or reduce performance; rather, it reshapes the emissions–performance trade-off by shifting the optimal emission threshold across firms.

These findings do not imply that emissions are beneficial; rather, they indicate that regulatory exposure influences the extent to which firms can manage emission-related costs through efficiency improvements, technological adaptation, and process optimisation. This pattern is consistent with the Porter Hypothesis, which posits that well-designed environmental regulation can enhance firm efficiency and innovation (Porter & van der Linde, 1995).

The results also align with Makridou et al. (2019), who show that regulatory environments that promote energy efficiency improve financial outcomes. Similarly, Oak and Bansal (2022) argue that such frameworks incentivise technological upgrades and reduce long-term exposure to energy-related risks.

The control variables exhibit largely consistent and theoretically aligned effects in both Table 3 and Table 4. Size shows a strong positive association with RoA across all quantiles, supporting the argument that larger firms benefit from economies of scale and superior access to resources. SG is generally positive and significant, indicating that expanding firms tend to exhibit improved financial performance. In contrast, financial leverage (LEV) is negatively associated with RoA, reflecting the adverse impact of higher financial risk on profitability.

Further, MTBV and TATR exert positive and significant effects, highlighting the importance of growth opportunities and operational efficiency in driving firm performance. The effect of firm age is mixed, turning negative at higher quantiles, suggesting that older firms may experience diminishing efficiency or rigidity at higher performance levels. The ESG score shows limited and inconsistent effects, reflecting the mixed evidence on the financial implications of ESG engagement in emerging markets.

Overall, the findings support Hypothesis 1, confirming the inverted U-shaped relationship between emissions and firm performance. They also support Hypothesis 2, demonstrating that environmental regulatory exposure moderates this relationship by shifting the turning point. Finally, the variation in turning points between lower- and higher-performing firms provides strong support for Hypothesis 3, indicating that the moderating effect of regulatory exposure is heterogeneous across the performance distribution.

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Insert Table 3

Insert Table 4

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### *4.3 Robustness analysis*

As a robustness check, the analysis is re-estimated using RoE as an alternative measure of CFP. The baseline results, reported in Table A.3, without the moderating variable, are consistent with the ROA findings in Table 3 and confirm a similar GhG-CFP relationship. Additionally, when ERE is incorporated as a moderating variable (see Table A.4), the moderating effect remains broadly consistent with the main results. The results for lower quantiles show that the turning point under regulatory exposure is lower than that for non-exposed firms, consistent with the main findings.

The only notable difference arises at the upper end of the performance distribution. Under the RoE specification, the turning point for higher-performing firms appears earlier, emerging from the 0.60 quantile, compared to the 0.80 quantile observed under ROA.

This difference reflects RoE's greater sensitivity to changes in profitability. As a measure of returns to equity holders, RoE amplifies the impact of earnings fluctuations, particularly in the presence of financial leverage, making the emissions–performance trade-off evident at lower performance levels.

Overall, the consistency of results across Tables A.3 and A.4 reinforces the robustness of the findings, while the earlier turning point under ROE highlights the role of financial structure in shaping the emissions–performance relationship.

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Insert Table A.3

Insert Table A.4

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### *1.1 Additional analysis*

Further, Table 5 presents the results of the two-step system GMM estimations, we employ GMM as a robustness test to address potential endogeneity in the GhG–CFP nexus. Since firm’s profitability may influence managers ability to invest in emission reduction processes, and in contrast emissions themselves may impact the financial performance. Therefore, using the estimates solely based on OLS or fixed-effects lead to biased estimates. Consequently, by using GMM framework we address these concerns by using an internal instrument (lag of dependent variable) and controlling for unobserved heterogeneity. The GMM results are consistent with the baseline quantile regressions and confirm a non-linear relationship between emissions and performance. Specifically, the coefficient of Ln(GhG) is positive and significant, while Ln(GhG)$^2$ is negative and significant, thereby supporting the inverted U-shaped pattern predicted by the Environmental Kuznets Curve.

The inclusion of the ERE variable and its interaction with emissions provides further evidence of regulatory moderation. The negative coefficient on the ERE dummy suggests that regulated firms initially face compliance costs, yet the positive and significant interaction term reveals that the ERE scheme shifts the turning point of the emissions–performance curve upward, similar to main findings.

The validity of the GMM estimates is supported by diagnostic tests, AR(1) is significant while AR(2) is not, indicating no second-order serial correlation, and the Sargan test p-values suggest that the instruments are valid. Turning point calculations further corroborate the moderating role of regulation, for Non-ERE firms the threshold occurs at approximately 2.74, whereas for ERE-regulated firms the turning point is delayed to around 3.22. Overall, the GMM results reinforce the robustness of the main findings.

Insert Table 5

## 2. Conclusion and Implications

This study examines the non-linear relationship between GhG emissions and CFP, while assessing the moderating role of ERE within the Indian context. Using a balanced panel of firms and quantile regression, the findings provide robust evidence that the emissions–performance relationship is not linear but follows an inverted U-shaped pattern. As highlighted in the empirical results, emissions initially contribute to improved firm performance, reflecting scale efficiencies and production expansion; however, beyond a threshold, the associated costs in the form of regulatory compliance, operational inefficiencies, and reputational risks outweigh these benefits.

Importantly, the study demonstrates that this relationship is not uniform across firms. The turning point varies across the performance distribution, indicating that lower-performing firms sustain the benefits of emissions for a longer period, whereas higher-performing firms encounter the emissions–performance trade-off earlier. This heterogeneity is further shaped by environmental regulatory exposure. The findings reveal that ERE shifts the turning point of the GhG–CFP relationship, extending the beneficial range of emissions for lower-performing firms while accelerating the trade-off for higher-performing firms. These results provide strong support for the Environmental Kuznets Curve (EKC) framework at the firm level and align with the Porter Hypothesis by demonstrating that regulatory mechanisms can influence firm behaviour through efficiency improvements and adaptive responses.

The study contributes to the literature in three key ways. First, it advances understanding of the emissions–performance nexus by incorporating a nonlinear, distributional perspective, highlighting that firm responses vary significantly across performance levels. Second, it introduces environmental regulatory exposure as a moderating mechanism, showing that regulation does not uniformly affect firms but instead reshapes the emissions–performance trade-off. Third, by integrating quantile regression with regulatory heterogeneity, the study provides a more nuanced explanation of how environmental and financial outcomes interact in emerging market contexts.

The findings have important managerial implications. Firms should recognise that emissions may generate short-term performance gains but entail long-term risks. Managers relying solely on aggregate performance indicators may overlook the timing of the emissions–performance trade-off. The results suggest that lower-performing firms can utilise regulatory frameworks to gradually improve efficiency, while higher-performing firms must adopt proactive emission control strategies, as they are more sensitive to regulatory and cost pressures. Additionally, the earlier emergence of the trade-off in the robustness analysis using ROE indicates that financial metrics reflecting shareholder returns can provide early signals of performance deterioration, enabling timely strategic adjustments.

From a policy perspective, the results suggest that environmental regulation should be designed with firm heterogeneity in mind. Market-based mechanisms such as the PAT scheme appear to facilitate gradual adjustment for less efficient firms while imposing necessary discipline on high-performing firms. This highlights the importance of flexible regulatory frameworks that encourage innovation and efficiency without imposing uniform constraints across all firms.

Despite its contributions, the study is subject to certain limitations. First, the measure of regulatory exposure is based on a binary classification, which may not fully capture the intensity and variation of regulatory pressures across firms. Second, regulatory exposure is not randomly assigned and is inherently linked to sectoral characteristics, which may introduce residual heterogeneity despite the inclusion of fixed effects and control variables. Third, the analysis relies on reported GhG emissions data, which may be subject to disclosure limitations, particularly in emerging markets. Finally, while the study establishes conditional relationships, it does not aim to identify causal effects of environmental regulation.

Future research can extend this analysis by employing alternative measures of regulatory intensity, incorporating dynamic policy changes, or adopting quasi-experimental designs to strengthen causal inference. Additionally, further investigation into the role of firm-level characteristics, such as technological capability and governance structures, may provide deeper insights into how firms respond to environmental regulation.

Overall, the study highlights that the relationship between emissions and financial performance is both non-linear and context-dependent, and that regulatory frameworks play a critical role in shaping this dynamic. These findings underscore the need for differentiated strategies at both the firm and policy levels to balance environmental sustainability with financial performance.

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**Table 1: Descriptive Statistics for GhG and CFP**

| Variables | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| **RoA** | 552 | 8.83 | 7.40 | 7.68 | -8.38 | 29.89 |
| **RoE** | 552 | 15.83 | 15.77 | 13.58 | -36.24 | 53.66 |
| **Ln(GhG)** | 552 | 2.58 | 2.45 | 1.13 | 0.43 | 4.80 |
| **Ln(GhG)$^2$** | 552 | 7.94 | 6.02 | 6.41 | 0.19 | 23.03 |
| **ERE** | 552 | 0.23 | 0.00 | 0.42 | 0.00 | 1.00 |
| **Size** | 552 | 5.51 | 5.52 | 0.55 | 4.34 | 6.90 |
| **Age** | 552 | 1.60 | 1.60 | 0.27 | 0.70 | 2.06 |
| **SG** | 552 | 12.16 | 9.38 | 21.91 | -36.49 | 111.07 |
| **LEV** | 552 | 21.74 | 17.02 | 18.84 | 0.00 | 76.42 |
| **MTBV** | 552 | 5.23 | 3.37 | 5.92 | 0.36 | 36.38 |
| **TATR** | 552 | 0.86 | 0.77 | 0.50 | 0.11 | 2.50 |
| **ESG** | 552 | 50.97 | 51.61 | 10.75 | 26.65 | 75.78 |

***Note(s):*** RoA = Return on Assets; RoE = Return on Equity; Ln(GhG) = natural logarithm of greenhouse gas emissions; Ln(GhG)$^2$ = square of greenhouse gas emissions; ERE = dummy variable for designated consumers (1 = DC firms, 0 = otherwise) under the PAT scheme; Size = natural logarithm of market capitalisation; Age = natural logarithm of firm age; SG = sales growth measured as log difference in sales; LEV = financial leverage, measured as the ratio of total liabilities to total assets; MTBV = market-to-book value ratio; TATR = total asset turnover ratio, measured as sales to total assets; ESG = ESG performance score obtained from Bloomberg.

**Table 2: Correlation Matrix for GhG and CFP**

| Variables | RoA | RoE | Ln(GhG) | ERE | Size | Age | SG | LEV | MTBV | TATR | ESG | VIF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **RoA** | 1 | | | | | | | | | | | |
| **RoE** | 0.822* | 1 | | | | | | | | | | |
| **Ln(GhG)** | -0.347* | -0.232* | 1 | | | | | | | | | 2.68 |
| **ERE** | -0.248* | -0.203* | 0.599* | 1 | | | | | | | | 1.81 |
| **Size** | 0.253* | 0.212* | 0.242* | -0.067 | 1 | | | | | | | 1.71 |
| **Age** | 0.081* | 0.077* | 0.091* | 0.039 | 0.103* | 1 | | | | | | 1.16 |
| **SG** | 0.116* | 0.111* | 0.019 | -0.004 | 0.142* | -0.144* | 1 | | | | | 1.07 |
| **LEV** | -0.639* | -0.400* | 0.409* | 0.248* | -0.109* | -0.224* | 0.043 | 1 | | | | 1.59 |
| **MTBV** | 0.506* | 0.468* | -0.397* | -0.268* | 0.206* | -0.094* | 0.118* | -0.193* | 1 | | | 1.58 |
| **TATR** | 0.584* | 0.605* | -0.272* | -0.304* | -0.004 | 0.103* | 0.082* | -0.405* | 0.392* | 1 | | 1.51 |
| **ESG** | -0.015 | -0.017 | 0.342* | 0.142* | 0.459* | 0.171* | 0.013 | 0.031 | -0.064 | -0.108* | 1 | 1.4 |

***Note(s):*** RoA = Return on Assets; RoE = Return on Equity; Ln(GhG) = natural logarithm of greenhouse gas emissions; ERE = dummy variable for designated consumers (1 = DC firms, 0 = otherwise) under the PAT scheme; Size = natural logarithm of market capitalisation; Age = natural logarithm of firm age; SG = sales growth measured as log difference in sales; LEV = financial leverage, measured as the ratio of total liabilities to total assets; MTBV = market-to-book value ratio; TATR = total asset turnover ratio, measured as sales to total assets; ESG = ESG performance score obtained from Bloomberg; VIF = Variance Inflation Factor. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

**Table 3: Quantile Regression Findings of the GhG-CFP Nexus by Employing ROA as a Proxy for CFP (Without PAT Regulation)**

| Variables | (0.1) | (0.2) | (0.3) | (0.4) | (0.5) | (0.6) | (0.7) | (0.8) | (0.95) |
|---|---|---|---|---|---|---|---|---|---|
| **Ln(GhG)** | 3.58*** | 1.35*** | 0.66*** | 0.45*** | 0.90*** | 1.71*** | 2.36*** | 2.56*** | 2.19*** |
| | (0.14) | (0.088) | (0.054) | (0.11) | (0.081) | (0.11) | (0.14) | (0.064) | (0.09) |
| **Ln(GhG)²** | -0.43*** | -0.19*** | -0.098** | -0.13*** | -0.21*** | -0.32*** | -0.44*** | -0.48*** | -0.35*** |
| | (0.023) | (0.015) | (0.008) | (0.017) | (0.018) | (0.022) | (0.025) | (0.014) | (0.017) |
| **Size** | 1.31*** | 1.35*** | 0.79*** | 1.10*** | 1.51*** | 1.89*** | 2.85*** | 3.05*** | 2.80*** |
| | (0.079) | (0.032) | (0.042) | (0.044) | (0.13) | (0.065) | (0.04) | (0.082) | (0.047) |
| **Age** | 0.90*** | 0.42*** | 0.33*** | -0.48*** | -0.25 | -0.68*** | -2.28*** | -2.05*** | -1.12*** |
| | (0.12) | (0.049) | (0.044) | (0.089) | (0.17) | (0.1) | (0.11) | (0.16) | (0.15) |
| **SG** | -0.0044** | 0.014*** | 0.022*** | 0.027*** | 0.028*** | 0.016*** | 0.0079*** | 0.017*** | 0.021*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.003) | (0.001) | (0.001) | (0.002) | (0.001) |
| **LEV** | -0.22*** | -0.16*** | -0.16*** | -0.13*** | -0.15*** | -0.16*** | -0.17*** | -0.19*** | -0.23*** |
| | (0.004) | (0.001) | (0.002) | (0.002) | (0.004) | (0.002) | (0.002) | (0.002) | (0.001) |
| **MTBV** | 0.34*** | 0.37*** | 0.38*** | 0.33*** | 0.39*** | 0.37*** | 0.34*** | 0.42*** | 0.48*** |
| | (0.016) | (0.004) | (0.004) | (0.004) | (0.006) | (0.004) | (0.005) | (0.005) | (0.005) |
| **TATR** | 3.32*** | 4.10*** | 4.41*** | 5.31*** | 4.45*** | 4.44*** | 5.06*** | 4.04*** | 3.58*** |
| | (0.08) | (0.047) | (0.051) | (0.054) | (0.16) | (0.076) | (0.033) | (0.046) | (0.064) |
| **ESG** | -0.040*** | 0.0078*** | 0.016*** | 0.016*** | 0.0026 | 0.0026 | -0.0076** | -0.017** | -0.0053 |
| | (0.004) | (0.002) | (0.002) | (0.004) | (0.005) | (0.003) | (0.003) | (0.004) | (0.003) |
| **Observations** | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 |
| **Turning Point (GhG*thousands of metric tons)** | **4.1628** | **3.5526** | **3.3673** | **1.7308** | **2.1429** | **2.6719** | **2.6818** | **2.6667** | **3.1286** |

Note(s): ROA denotes Return on Assets. Ln(GhG) represents the natural logarithm of greenhouse gas emissions, and Ln(GhG)² denotes its squared term, capturing the non-linear relationship. SIZE is measured as market capitalization, AGE refers to the number of years since firm incorporation, SG represents sales growth, LEV denotes leverage, MTBV refers to market-to-book value ratio, TATR represents total asset turnover ratio, and ESG captures environmental, social, and governance performance. Turning points are computed based on the estimated coefficients of Ln(GhG) and Ln(GhG)Sq, indicating the emission threshold at which the relationship between emissions and firm performance changes direction. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 4: Quantile Regression Findings of the GhG-CFP Nexus by Employing ROA as a proxy for CFP (With ERE)**

| Variables | (0.1) | (0.2) | (0.3) | (0.4) | (0.5) | (0.6) | (0.7) | (0.8) | (0.95) |
|---|---|---|---|---|---|---|---|---|---|
| **Ln(GhG)** | 3.57*** | 3.43*** | 2.42*** | 0.81*** | 1.14*** | 2.71*** | 3.20*** | 3.10*** | 2.29*** |
| | (0.097) | (0.057) | (0.12) | (0.041) | (0.042) | (0.057) | (0.06) | (0.19) | (0.16) |
| **Ln(GhG)²** | -0.68*** | -0.75*** | -0.64*** | -0.45*** | -0.52*** | -0.80*** | -0.81*** | -0.67*** | -0.34*** |
| | (0.016) | (0.01) | (0.014) | (0.0078) | (0.01) | (0.014) | (0.016) | (0.066) | (0.025) |
| **ERE** | -11.0*** | -7.61*** | 0.49* | -0.96** | 0.68*** | 1.06*** | -0.03 | 1.24* | 3.81*** |
| | (0.22) | (0.17) | (0.22) | (0.29) | (0.12) | (0.21) | (0.24) | (1.1) | (0.8) |
| **Ln(GhG)*ERE** | 3.45*** | 2.55*** | 0.86*** | 1.22*** | 0.92*** | 1.45*** | 0.96*** | 0.26 | -0.61** |
| | (0.075) | (0.048) | (0.06) | (0.072) | (0.04) | (0.059) | (0.064) | (0.32) | (0.2) |
| **Size** | 1.66*** | 2.57*** | 2.69*** | 2.80*** | 3.12*** | 2.96*** | 3.19*** | 2.84*** | 1.56*** |
| | (0.094) | (0.019) | (0.06) | (0.028) | (0.028) | (0.039) | (0.015) | (0.13) | (0.24) |
| **Age** | -0.20* | 0.49*** | -0.26*** | -1.16*** | -1.03*** | -1.61*** | -2.38*** | -3.13*** | -3.36*** |
| | (0.085) | (0.034) | (0.032) | (0.044) | -0.046 | -0.03 | -0.054 | -0.12 | -0.24 |
| **SG** | 0.0063*** | 0.012*** | 0.022*** | 0.015*** | 0.0046*** | 0.020*** | 0.019*** | 0.0012 | 0.027*** |
| | (0.0011) | (0.00047) | (0.00053) | (0.0008) | (0.00082) | (0.00075) | (0.00048) | (0.0033) | (0.0027) |
| **LEV** | -0.18*** | -0.16*** | -0.14*** | -0.14*** | -0.15*** | -0.15*** | -0.17*** | -0.18*** | -0.29*** |
| | (0.0013) | (0.00037) | (0.0014) | (0.00075) | (0.00099) | (0.00059) | (0.00059) | (0.0017) | (0.0035) |
| **MTBV** | 0.28*** | 0.25*** | 0.32*** | 0.30*** | 0.30*** | 0.31*** | 0.34*** | 0.43*** | 0.45*** |
| | (0.0057) | (0.0028) | (0.0039) | (0.0017) | (0.002) | (0.0022) | (0.0046) | (0.016) | (0.01) |
| **TATR** | 4.55*** | 4.54*** | 4.77*** | 5.42*** | 5.13*** | 5.37*** | 5.32*** | 4.58*** | 2.90*** |
| | (0.15) | (0.031) | (0.041) | (0.036) | (0.02) | (0.027) | (0.02) | (0.15) | (0.07) |
| **ESG** | -0.019*** | -0.020** | -0.011** | -0.0062* | -0.019*** | -0.0050** | -0.010** | 0.000097 | 0.034*** |
| | (0.0012) | (0.0014) | (0.0013) | (0.0011) | (0.0016) | (0.00071) | (0.00094) | (0.0037) | (0.0068) |
| **Observations** | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 |
| **Turning Point (GhG*thousands of metric tons Regulatory Non-Exposure=0)** | **2.63** | **2.29** | **1.89** | **0.9** | **1.1** | **1.69** | **1.98** | **2.31** | **3.37** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Turning Point (GhG*thousands of metric tons Regulatory Exposure =1)** | **5.16** | **3.99** | **2.56** | **2.26** | **1.98** | **2.6** | **2.58** | **2.5** | **2.47** |

Note(s): RoA = Return on Assets; Ln(GhG) = natural logarithm of greenhouse gas emissions; $Ln(GhG)^2$ = square of greenhouse gas emissions; ERE = dummy variable for designated consumers (1 = DC firms, 0 = otherwise) under the PAT scheme; Ln(GhG) × ERE = interaction term capturing the moderating effect of regulatory exposure; Size = natural logarithm of market capitalisation; Age = natural logarithm of firm age; SG = sales growth measured as log difference in sales; LEV = financial leverage, measured as the ratio of total liabilities to total assets; MTBV = market-to-book value ratio; TATR = total asset turnover ratio, measured as sales to total assets; ESG = ESG performance score obtained from Bloomberg. Turning points are computed as $-\beta 1/2\beta 2$ and reported separately for firms with no regulatory exposure (PAT = 0) and regulatory exposure (PAT = 1). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5 Dynamic Panel Regression Results for GhG and CFP (ROA): With and Without Moderating Effect of ERE**

| Variables | Without interaction | With interaction |
|---|---|---|
| **Ln(GhG)** | 4.55* | 3.94** |
| | (2.21) | (1.47) |
| **Ln(GhG)²** | -0.83** | -1.12** |
| | (0.44) | (0.35) |
| **ERE** | - | -7.88** |
| | | (3.01) |
| **Ln(GhG)*ERE** | - | 3.27** |
| | | (1.24) |
| **Size** | 1.44 | 2.89*** |
| | (0.85) | (0.83) |
| **AGE** | 0.44 | 0.44 |
| | (1.22) | (1.13) |
| **SG** | 0.024* | 0.0026 |
| | (0.011) | (0.012) |
| **LEV** | -0.12*** | -0.10*** |
| | (0.034) | (0.023) |
| **MTBV** | 0.19* | 0.15** |
| | (0.09) | (0.054) |
| **TATR** | 3.04** | 3.88** |
| | (1.12) | (1.33) |
| **ESG** | -0.023 | -0.069* |
| | (0.042) | (0.032) |
| **No of observations** | 368 | 368 |
| **AR(1)** | 0.000 | 0.001 |
| **AR(2)** | 0.487 | 0.746 |
| **Sargan test of overrid. Restrictions:** | 0.471 | 0.438 |
| **Turning Point (GhG*thousands of metric tons)** | **2.741** | **-** |
| **Turning Point (GhG*thousands of metric tons Regulatory Non-Exposure=0)** | **-** | **1.759** |
| **Turning Point (GhG*thousands of metric tons Regulatory Exposure =1)** | **-** | **3.219** |

Note(s): RoA = Return on Assets; Ln(GhG) = natural logarithm of greenhouse gas emissions; Ln(GhG)² = square of greenhouse gas emissions; ERE = dummy variable for designated consumers (1 = DC firms, 0 = otherwise) under the PAT scheme; Ln(GhG) × ERE = interaction term capturing the moderating effect of regulatory exposure; Size = natural logarithm of market capitalisation; Age = natural logarithm of firm age; SG = sales growth measured as log difference in sales; LEV = financial leverage, measured as the ratio of total liabilities to total assets; MTBV = market-to-book value ratio; TATR = total asset turnover ratio, measured as sales to total assets; ESG = ESG performance score obtained from Bloomberg. AR(1) and AR(2) represent Arellano–Bond tests for first- and second-order serial correlation, respectively; Sargan test refers to the test of over-identifying restrictions. Turning points are computed as $-\beta 1/2\beta 2$, with separate estimates reported for models without interaction and for firms with regulatory non-exposure (PAT = 0) and regulatory exposure (PAT = 1). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

**Appendix**
**Table A.1: A Systematic Literature Review**

| Authors (Year) | Objective | Country | Methodology | Key finding(s) |
|---|---|---|---|---|
| Panel A. Prior evidence on GHG emissions and corporate financial performance (CFP) | | | | |
| **(Gerged et al., 2020)** | **Test whether mandatory GhG disclosure is associated with firms' cost of equity and whether the relation is non-linear** | **UK** | **Panel regressions under mandatory regime (post-2013), non-linear (quadratic) specification** | **U-shaped relation between GhG emissions and cost of equity: risk first rises then falls beyond a threshold, consistent with non-linear trade-offs.** |
| **(Ghosh et al., 2023)** | **Examine how carbon performance (CP) and disclosure affect CFP allowing for non-linearity** | **India** | **OLS, and Fixed effect** | **Initial stage CP decreases CFP but later improves CFP indicating a U-shaped relationship.** |
| **(Le & Nguyen-Phung, 2024)** | **To evaluate how environmental performance influences corporate financial performance in African emerging markets** | **Africa** | **Fixed effect panel data regressions; GMM estimators to address endogeneity, 2SLS** | **GhG emission intensity had a significantly negative impact on ROA and ROE; effects stronger in high-emission sectors. Results robust across instruments and post-Paris Agreement period.** |
| **Trumpp & Guenther (2015)** | **Explore potential U-shaped relationships between Corporate Environmental Performance (CEP) and CFP** | **Cross-industry listed firms (CDP Global 500, S&P 500, FTSE 350)** | **Panel regressions Fixed effect with quadratic terms** | **Companies with low CEP experience negative relationship, whereas higher CEP demonstrate positive effect. The study demonstrates U-shaped relationship.** |
| **Panel B. Emissions Trading Schemes (ETS) and firm performance** | | | | |

| | | | | |
|---|---|---|---|---|
| **(Commins et al., 2011)** | **Assess impact of climate policy stringency on firm performance** | **EU** | **Econometric analysis on firm-level panel** | **Stricter climate policies are associated with lower return-on-capital for trade-exposed manufacturing firms. The impact on productivity and profits are negative.** |
| **(Oak & Bansal, 2022)** | **To evaluate the effectiveness of the PAT scheme in improving energy efficiency among designated industries** | **India** | **Policy and empirical assessment of PAT cycles** | **PAT led to improvements in energy efficiency, though benefits varied across industries; compliance costs and uneven enforcement limited full effectiveness.** |
| **(Chauhan & Thangavel, 2025)** | **To analyse how PAT contributes to industrial energy efficiency and sustainability outcomes** | **India** | **Sectoral case analysis and policy review** | **PAT incentivized adoption of energy-efficient technologies; uneven sectoral benefits. Stronger monitoring and integration with carbon markets needed.** |
| **(Yu et al., 2021)** | **To test whether ETS improves both emission reduction and firm financial performance** | **China; A-share listed industrial firms** | **Panel regression, firm-level ETS participation** | **ETS firms reduced carbon emissions and showed improved financial performance.** |
| **(Μακρίδου et al., 2019)** | **To examine profitability drivers of ETS-covered firms** | **EU** | **Firm-level panel regression** | **Profitability of ETS firms linked to allocation factors and emission intensity.** |

**Source: Author’s own compilation**

**Table A.2: Description of Research Variables**

| Variables | Name | Description | Citations |
|---|---|---|---|
| **ROA** | Return on Assets | Net income divided by total assets; widely used accounting-based measure of corporate financial performance | Hart & Ahuja (1996); Fujii et al. (2013) |
| **ROE** | Return on Equity | Net income divided by shareholders' equity; captures returns to shareholders | Lewandowski (2017) |
| **Ln(GhG)** | Log of Greenhouse Gas Emissions | Natural logarithm of firm-level total GhG emissions (Scope 1 and 2); captures scale of emissions | Broadstock et al. (2017) |
| **Ln(GhG)²** | Quadratic Emissions Term | Squared term of Ln(GhG); used to test for curvilinear (U-shaped or inverted U-shaped) relationships | Broastock et al. (2017); Trumpp & Guenther (2015) |
| **ERE** | Environment Regulatory Exposure (Dummy) | Equals 1 if firm is PAT-compliant, 0 otherwise; captures participation in India's energy efficiency trading scheme | Bureau of Energy Efficiency (BEE), Govt. of India |
| **Ln(GhG)*ERE** | Interaction Term | Product of Ln(GhG) and ERE dummy; tests whether ERE moderates the emissions–performance link | Porter & van der Linde (1995) for theoretical basis |
| **Size** | Firm Size | Natural logarithm of market capitalization; used as a proxy for firm scale and market valuation. This capture both firm size and the extent of investor scrutiny, consistent with ESG–finance studies. | Broadstock et al. (2017); contrast Clarkson et al. (2010) |
| **Leverage (LEV)** | Leverage Ratio | Total debt divided by total assets; controls for capital structure and financial risk | Fujii et al. (2013) |
| **MTBV** | Market-to-Book Value | Ratio of market capitalization to book value of equity; proxy for growth opportunities | Broadstock et al. (2018) |

| | | | |
|---|---|---|---|
| **Total Asset Turnover Ratio (TATR)** | Efficiency Ratio | Sales divided by total assets; proxy for operational efficiency and utilization of resources | Hart & Ahuja (1996) |
| **ESG** | ESG Score | Composite measure of environmental, social, and governance practices. | Rao et al. (2023) |
| **Age** | Firm Age | Number of years since incorporation or listing; controls for maturity and lifecycle stage | Trumpp & Guenther (2015) |
| **Sales Growth (SG)** | Sales Growth Rate | Year-on-year percentage change in sales revenue; controls for firm growth dynamics | Lewandowski (2017) |

**Notes:** The variables for Indian listed companies from 2017 to 2022 are extracted from Bloomberg and the company's financial statements.

**Table A.3: Quantile Regression Findings of the GhG-CFP Nexus by Employing ROE as a Proxy for CFP (Without ERE)**

| Variables | (0.1) | (0.2) | (0.3) | (0.4) | (0.5) | (0.6) | (0.7) | (0.8) | (0.95) |
|---|---|---|---|---|---|---|---|---|---|
| **Ln(GhG)** | -0.048 | 2.74*** | 0.89*** | 0.66*** | 2.22*** | 4.76*** | 6.23*** | 6.57*** | 7.59*** |
| | (0.19) | (0.15) | (0.11) | (0.095) | (0.091) | (0.055) | (0.074) | (0.14) | (0.35) |
| **Ln(GhG)²** | 0.079* | -0.50*** | -0.14*** | -0.18*** | -0.43*** | -0.85*** | -1.09*** | -1.19*** | -1.17*** |
| | (0.032) | (0.029) | (0.023) | (0.017) | (0.016) | (0.008) | (0.011) | (0.031) | (0.077) |
| **Size** | 5.11*** | 5.05*** | 4.47*** | 4.65*** | 2.85*** | 2.86*** | 2.64*** | 2.91*** | 3.97*** |
| | (0.04) | (0.3) | (0.17) | (0.043) | (0.088) | (0.048) | (0.12) | (0.081) | (0.15) |
| **Age** | 0.46*** | 1.05*** | -0.51*** | -0.76*** | -0.70*** | -1.66*** | -2.61*** | -3.78*** | -5.00*** |
| | (0.098) | (0.13) | (0.11) | (0.12) | (0.095) | (0.083) | (0.11) | (0.11) | (0.53) |
| **SG** | 0.032*** | 0.0077 | 0.0078* | 0.00067 | 0.000052 | -0.0020** | -0.00026 | 0.013*** | 0.070*** |
| | (0.001) | (0.005) | (0.004) | (0.002) | (0.003) | (0.000) | (0.001) | (0.001) | (0.003) |
| **LEV** | -0.34*** | -0.16*** | -0.11*** | -0.062*** | -0.051** | -0.011*** | -0.018** | 0.018*** | -0.012* |
| | (0.003) | (0.005) | (0.001) | (0.005) | (0.002) | (0.002) | (0.002) | (0.003) | (0.006) |
| **MTBV** | 0.46*** | 0.50*** | 0.53*** | 0.53*** | 0.65*** | 0.66*** | 0.71*** | 0.70*** | 0.70*** |
| | (0.005) | (0.023) | (0.01) | (0.004) | (0.01) | (0.002) | (0.005) | (0.004) | (0.011) |
| **TATR** | 11.9*** | 10.6*** | 11.6*** | 12.2*** | 12.0*** | 12.6*** | 11.3*** | 12.0*** | 11.2*** |
| | (0.054) | (0.23) | (0.067) | (0.054) | (0.083) | (0.029) | (0.078) | (0.079) | (0.073) |
| **ESG** | -0.21*** | -0.100** | 0.040*** | 0.031*** | 0.071*** | 0.041*** | -0.0035 | -0.042** | -0.055** |
| | (0.003) | (0.009) | (0.005) | (0.002) | (0.002) | (0.001) | (0.004) | (0.006) | (0.018) |
| **Observations** | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 |
| **Turning Point (GhG*thousands of metric tons)** | **NR** | **2.74** | **3.178** | **1.8333** | **2.581** | **2.8** | **2.853** | **2.761** | **3.24** |

Note(s): ROE denotes Return on Equity. Ln(GhG) represents the natural logarithm of greenhouse gas emissions, and Ln(GhG)² denotes its squared term, capturing the non-linear relationship. SIZE is measured as market capitalization, AGE refers to the number of years since firm incorporation, SG represents sales growth, LEV denotes leverage, MTBV refers to market-to-book value ratio, TATR represents total asset turnover ratio, and ESG captures environmental, social, and governance performance. Turning points are computed based on the estimated coefficients of Ln(GhG) and Ln(GhG)Sq, indicating the emission threshold at which the relationship between emissions and firm performance changes direction. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A.4: Quantile Regression Findings of the GhG-CFP Nexus by Employing ROE as a Proxy for CFP (With ERE)**

| Variables | (0.1) | (0.2) | (0.3) | (0.4) | (0.5) | (0.6) | (0.7) | (0.8) | (0.95) |
|---|---|---|---|---|---|---|---|---|---|
| **Ln(GhG)** | 1.05*** | 1.41*** | 1.48*** | 0.96*** | 1.91*** | 3.71*** | 1.22*** | 6.06*** | 0.007 |
| | (0.031) | (0.220) | (0.015) | (0.058) | (0.19) | (0.054) | (0.16) | (0.41) | (0.078) |
| **$Ln(GhG)^2$** | -0.16** | -0.36** | -0.59*** | -0.50*** | -0.57*** | -0.86*** | 0.12** | -0.97*** | 0.84*** |
| | (0.0063) | (0.044) | (0.0024) | -0.0097 | -0.025 | -0.014 | -0.041 | -0.083 | -0.02 |
| **ERE** | -3.28*** | 1.89*** | 2.90*** | 4.87*** | 8.84*** | 6.60*** | 16.1*** | 7.52*** | 20.9*** |
| | (0.16) | (0.42) | (0.043) | (0.13) | (0.35) | (0.12) | (0.45) | (0.49) | (0.23) |
| **Ln(GhG)*ERE** | 1.08*** | 0.52*** | 0.75*** | 0.083* | -1.18*** | -0.82*** | -4.84*** | -1.71*** | -6.20*** |
| | (0.049) | (0.14) | (0.014) | (0.033) | (0.075) | (0.046) | (0.16) | (0.18) | (0.063) |
| **Size** | 4.98*** | 5.35*** | 6.19*** | 5.58*** | 4.08*** | 3.46*** | 2.95*** | 2.72*** | -0.19** |
| | (0.03) | (0.099) | (0.015) | (0.02) | (0.045) | (0.052) | (0.074) | (0.088) | (0.065) |
| **Age** | 0.015 | 0.82*** | 0.17*** | -0.02 | -0.47*** | -2.18*** | -0.41** | -4.96*** | -6.79*** |
| | (0.03) | (0.097) | (0.033) | (0.072) | (0.11) | (0.058) | (0.13) | (0.19) | (0.073) |
| **SG** | -0.0029* | 0.0043 | -0.011*** | -0.011** | 0.013*** | 0.0047*** | 0.0063*** | -0.0022 | 0.028*** |
| | (0.00064) | (0.0033) | (0.00028) | (0.0016) | (0.0033) | (0.00066) | (0.0018) | (0.0043) | (0.001) |
| **LEV** | -0.32*** | -0.14** | -0.086*** | -0.043** | -0.014** | 0.0042*** | 0.018*** | 0.010*** | -0.077*** |
| | (0.00049) | (0.0039) | (0.00031) | (0.001) | (0.0031) | (0.00099) | (0.0039) | (0.0024) | (0.0019) |
| **MTBV** | 0.46*** | 0.50*** | 0.39*** | 0.42*** | 0.59*** | 0.67*** | 0.69*** | 0.84*** | 0.89*** |
| | (0.0035) | (0.0082) | (0.0015) | (0.0047) | (0.0073) | (0.0057) | (0.0048) | (0.0059) | (0.0062) |
| **TATR** | 12.4*** | 10.5*** | 13.9*** | 14.3*** | 13.1*** | 11.9*** | 12.3*** | 12.4*** | 11.8*** |
| | (0.033) | (0.13) | (0.026) | (0.072) | (0.095) | (0.045) | (0.17) | (0.098) | (0.034) |
| **ESG** | -0.18*** | -0.094* | 0.0088*** | 0.015*** | 0.025*** | 0.023*** | 0.036*** | -0.014* | -0.084*** |
| | (0.0016) | (0.0034) | (0.00052) | (0.0016) | (0.0053) | (0.0022) | (0.0033) | (0.006) | (0.0023) |
| **Observations** | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 | 552 |
| **Turning Point (GhG*thousands of metric tons Regulatory Non-Exposure=0)** | **3.28** | **1.96** | **1.25** | **0.96** | **1.68** | **2.16** | **NA** | **3.12** | **NA** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Turning Point (GhG*thousands of metric tons Regulatory Exposure =1)** | **6.66** | **2.68** | **1.89** | **1.04** | **0.64** | **1.69** | **NA** | **2.24** | **NA** |

Note(s): RoE = Return on Equity; Ln(GhG) = natural logarithm of greenhouse gas emissions; $Ln(GhG)^2$ = square of greenhouse gas emissions; ERE = dummy variable for designated consumers (1 = DC firms, 0 = otherwise) under the PAT scheme; Ln(GhG) × ERE = interaction term capturing the moderating effect of regulatory exposure; Size = natural logarithm of market capitalisation; Age = natural logarithm of firm age; SG = sales growth measured as log difference in sales; LEV = financial leverage, measured as the ratio of total liabilities to total assets; MTBV = market-to-book value ratio; TATR = total asset turnover ratio, measured as sales to total assets; ESG = ESG performance score obtained from Bloomberg. Turning points are computed as $-\beta 1/2\beta 2$ and reported separately for firms with no regulatory exposure (PAT = 0) and regulatory exposure (PAT = 1). Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.