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The Interplay between Carbon Intensity, Artificial Intelligence Innovation, Systematic Risk, and Unsystematic Risk

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Abstract

Carbon intensity has emerged as a critical financial risk factor in Indonesia amid the implementation of carbon economic policies, including Presidential Regulation No. 98 of 2021 and the launch of the Indonesia Carbon Exchange in 2023. This study examines the effect of carbon intensity on firm risk, measured through systematic risk and unsystematic risk, and investigates the moderating role of Artificial Intelligence (AI) innovation among companies listed on the Indonesia Stock Exchange over the period 2018–2024. Using panel data regression analysis with year fixed effects on 394 firm-year observations across 74 companies, carbon intensity is measured as CO_2 emissions divided by firm revenue, systematic risk is represented by stock beta, unsystematic risk is measured through residual volatility, and AI innovation is proxied by the natural logarithm of AI-related patent counts. The results show that carbon intensity has a positive and significant effect on both systematic risk and unsystematic risk, indicating that firms with higher carbon exposure face greater market sensitivity and firm-specific volatility. Furthermore, AI innovation significantly weakens the positive effect of carbon intensity on unsystematic risk, suggesting its role as a firm-level risk-absorbing mechanism during the carbon transition process. However, AI innovation does not significantly moderate the relationship between carbon intensity and systematic risk, indicating that macro-level carbon transition risks remain beyond the reach of individual firm-level technological capabilities. This study contributes to the literature by providing empirical evidence from an emerging market setting and by highlighting the differentiated moderating role of AI innovation across two dimensions of firm risk.
Keywords: Carbon intensity, Firm Risk, Unsystematic Risk, Systematic Risk, AI Innovation.

Abstrak

Intensitas karbon telah menjadi faktor risiko keuangan yang penting di Indonesia seiring penerapan kebijakan ekonomi karbon, termasuk Perpres No. 98 Tahun 2021 dan peluncuran Bursa Karbon Indonesia pada tahun 2023. Penelitian ini bertujuan untuk menguji pengaruh intensitas karbon terhadap risiko perusahaan yang diukur melalui risiko sistematis dan risiko tidak sistematis, serta menganalisis peran moderasi Inovasi Kecerdasan Buatan (AI) pada perusahaan yang terdaftar di Bursa Efek Indonesia periode 2018–2024. Dengan menggunakan analisis regresi data panel dengan year fixed effects pada 394 observasi firm-year dari 74 perusahaan, intensitas karbon diukur sebagai emisi CO_2 dibagi pendapatan perusahaan, risiko sistematis direpresentasikan oleh beta saham, risiko tidak sistematis diukur melalui volatilitas residual, dan inovasi AI diproksikan menggunakan logaritma natural jumlah paten berbasis AI. Hasil penelitian menunjukkan bahwa intensitas karbon berpengaruh positif dan signifikan terhadap risiko sistematis maupun risiko tidak sistematis, mengindikasikan bahwa perusahaan dengan paparan karbon lebih tinggi menghadapi sensitivitas pasar dan volatilitas spesifik perusahaan yang lebih besar. Selain itu, inovasi AI terbukti secara signifikan memperlemah pengaruh positif intensitas karbon terhadap risiko tidak sistematis, yang menunjukkan perannya sebagai mekanisme penyerap risiko di tingkat perusahaan selama proses transisi karbon. Namun, inovasi AI tidak secara signifikan memoderasi hubungan antara intensitas karbon dan risiko sistematis, mengindikasikan bahwa risiko transisi karbon di tingkat makro tetap berada di luar jangkauan kemampuan teknologi perusahaan secara individual. Penelitian ini berkontribusi pada literatur dengan memberikan bukti empiris dari konteks pasar berkembang dan menyoroti peran moderasi inovasi AI yang berbeda pada dua dimensi risiko perusahaan.
Keywords: *Intensitas Karbon, Risiko perusahaan, Risiko tidak sistematis, Risiko sistematis, Inovasi Kecerdasan Buatan.*

INTRODUCTION

Global carbon emissions continue to rise at an alarming rate. According to the International Energy Agency IEA (2025), global CO_2 emissions from energy reached a record high of 37.4 billion tonnes in 2023, with emerging markets accounting for an increasingly large share of total emissions. At the same time, capital markets worldwide are beginning to price carbon exposure into asset valuations, as institutional investors and regulators increasingly demand transparency regarding firms' environmental risk profiles (Bolton et al., 2021). In this context, carbon intensity defined as the volume of carbon emissions relative to firm revenue has emerged as a critical indicator of a company's vulnerability to carbon-related financial risks, including regulatory costs, transition risks, and shifts in investor preferences toward sustainable assets (Bolton et al., 2021; Chen et al., 2025).

Indonesia represents a particularly important and underexplored context for studying these dynamics. As one of the world's largest greenhouse gas emitters and a major coal-producing economy, Indonesia faces significant pressure to decarbonize its economic activities while sustaining growth. The Indonesian government has ratified the Paris Agreement through Law No. 16 of 2016, committing to reduce emissions by 31.89% independently or 43.2% with international support by 2030. These commitments have been operationalized through Presidential Regulation No. 98 of 2021 on the Carbon Economic Value (Perpres No. 98/2021) and Law No. 7 of 2021 on Harmonization of Tax Regulations (UU HPP), which together establish the regulatory foundation for carbon taxes and carbon trading mechanisms in Indonesia. A landmark development followed in September 2023, when Indonesia launched the Indonesia Carbon Exchange (IDXCarbon), marking the operationalization of a domestic carbon market and signaling a new era of carbon risk pricing for Indonesian listed companies (OJK. 2023). In parallel, the Financial Services Authority (OJK) has mandated sustainability reporting for publicly listed companies through OJK Regulation No. 51/POJK.03/2017, reinforcing environmental disclosure obligations across the Indonesia Stock Exchange (IDX) (OJK, 2017). These regulatory developments collectively heighten the relevance of carbon intensity as a financial risk variable for firms listed on the IDX, regardless of sector.

Empirical evidence from global markets suggests that carbon intensity is associated with elevated corporate risk. Firms with higher carbon exposure tend to face greater regulatory costs, operational uncertainty, and declining investor confidence, which can translate into both higher market-wide risk (systematic risk) and firm-specific volatility (unsystematic risk) (Al-Fakir Al Rabab'a et al., 2024; Bolton et al., 2021; Schuster et al., 2025). Data from the IDX further illustrate this challenge: the carbon intensity of sample firms in this study ranges from as low as 48.884 to as high as 116,258.583 tonnes of CO_2 per billion rupiah of revenue, with a mean of 6,425.322, reflecting enormous heterogeneity in carbon exposure among Indonesian listed firms. This wide variation suggests that the financial implications of carbon intensity are not uniform across firms and warrant rigorous empirical investigation.

However, prior research on the relationship between carbon intensity and corporate risk yields inconsistent findings. Several studies confirm that higher carbon exposure increases both systematic and unsystematic risk (Bolton et al., 2021; Enders et al., 2025; Schuster et al., 2025) while others find that this relationship is weak or sector-dependent, moderated by institutional quality, disclosure practices, and corporate governance (Al-Fakir Al Rabab'a et al., 2024; Haryanto et al., 2025; Ozkan et al., 2023; Y. Wang et al., 2022). These inconsistencies suggest that the impact of carbon intensity on corporate risk is context-sensitive and may be shaped by firm-level characteristics and strategic responses, including technological adaptation.

On the other hand, the emergence of Artificial Intelligence (AI) technology introduces a new dimension to corporate risk management. AI innovation proxied in this study through firms' AI-related patent activity has been shown to improve energy efficiency, optimize operational processes, and strengthen environmental risk management capabilities, thereby potentially mitigating the financial impact of carbon intensity (Li et al., 2021; Zhang et al., 2025). At the same time, AI adoption may also increase systematic risk by deepening firms' integration with market dynamics and digital infrastructure dependencies (Tian et al., 2024; Wu & Zhou, 2025). This dual nature of AI innovation makes it a theoretically and empirically compelling moderating variable in the carbon intensity–firm risk relationship.

Despite the growing body of literature, several important research gaps remain. First, most prior studies examine either systematic risk or unsystematic risk in isolation, with limited research simultaneously addressing both dimensions of firm risk. Second, the moderating role of AI innovation on the relationship between carbon intensity and firm risk remains underexplored, particularly in emerging market settings. Third, the majority of existing studies are concentrated in developed economies or large emerging markets such as China, with Indonesia despite its distinct regulatory environment, rapidly evolving carbon market, and diverse listed firm population remaining largely underrepresented in this literature. Specifically, the combined effect of Indonesia's new carbon pricing instruments, IDXCarbon, and mandatory sustainability reporting on firm-level risk among IDX-listed companies has not been empirically examined.

This study therefore aims to fill these gaps by examining: (1) the effect of carbon intensity on systematic risk and unsystematic risk among companies listed on the Indonesia Stock Exchange (IDX) over the period 2018–2024; and (2) the moderating role of AI innovation in this relationship. The sample covers all listed firms with available carbon emission and AI patent data, regardless of profitability status, as the study focuses on firm risk rather than firm performance. The findings are expected to contribute empirical evidence from an emerging market setting, while also providing practical insights for firms, investors, and policymakers navigating the carbon transition in Indonesia.

LITERATURE REVIEW

Grand Theory

This study is grounded in three complementary theoretical frameworks that collectively explain the relationship between carbon intensity, firm risk, and AI innovation. The first is Ethical Investing Theory, developed by Heinkel et al. (2015). which provides the foundational logic for understanding how carbon-related factors influence corporate risk through capital market mechanisms. In this model, environmentally oriented investors referred to as green investors systematically exclude firms with high pollution levels from their portfolios. This exclusion reduces demand for the shares of carbon-intensive firms, lowering stock prices, raising the cost of capital, and reducing risk diversification benefits, which together elevate firm risk. The theory implies that firms failing to manage carbon intensity will face increasing financial disadvantage as the proportion of green investors in capital markets grows, which is particularly relevant in the context of Indonesia's evolving carbon regulation and the launch of IDXCarbon in 2023.

The second is Social Norms Theory, advanced by Hong & Kacperczyk (2009) through their study of sin stocks. This theory demonstrates that prevailing social norms regarding sustainability and environmental responsibility directly shape investor behavior and asset pricing. Firms operating in industries considered environmentally or socially harmful tend to be systematically avoided by institutional investors, resulting in lower institutional ownership, reduced analyst coverage, and higher required returns as compensation for reputational and exclusion risks. In the context of this study, social norms theory explains why firms with high carbon intensity perceived as inconsistent with sustainability norms may experience elevated unsystematic risk through increased stock price volatility and investor uncertainty, as well as higher systematic risk through their co-movement with broader environmental policy shocks.

The third is Resource-Based View (RBV) Theory, as developed by Lockett & Thompson (2009), which provides the theoretical basis for understanding AI innovation as a firm-level strategic resource. RBV posits that firms possessing rare, valuable, inimitable, and non-substitutable resources are better positioned to achieve sustained competitive advantage and manage environmental uncertainties. AI innovation represents precisely such a strategic resource: firms with advanced AI capabilities can leverage machine learning, predictive analytics, and intelligent process automation to improve operational efficiency, enhance environmental risk monitoring, and adapt more effectively to carbon regulatory changes. This theory supports the expectation that AI innovation moderates the relationship between carbon intensity and firm risk by enabling firms to convert carbon exposure into manageable, efficiency-driven outcomes rather than uncontrolled financial vulnerabilities.

Together, these three theories form an integrated framework: Ethical Investing Theory and Social Norms Theory explain *why* carbon intensity elevates both systematic and unsystematic risk through investor behavior and market pricing mechanisms, while Resource-Based View Theory

explains *how* AI innovation can attenuate this relationship by strengthening firms' adaptive capabilities and strategic resilience.

Literature Review

Carbon intensity describes the volume of carbon emissions generated per unit of firm revenue, and represents a firm's exposure to financial risks arising from carbon emission reduction policies, environmental regulations, and the transition toward a low-carbon economy (Bolton et al., 2021) As regulatory pressure intensifies globally and investor preferences increasingly favor sustainable assets, financial markets have begun to integrate carbon intensity into the process of assessing firm risk and pricing corporate assets (Bolton et al., 2021). Firms with high carbon intensity face a compounding set of financial pressures: rising compliance costs associated with carbon pricing mechanisms, potential asset stranding in fossil fuel-dependent sectors, reputational risks from environmental controversies, and the prospect of higher capital costs as green investors reallocate their portfolios away from carbon-intensive assets (Enders et al., 2025; Schuster et al., 2025).

From a theoretical standpoint, Ethical Investing Theory (Heinkel et al., 2015) explains that green investors' systematic exclusion of carbon-intensive firms reduces share demand, increases cost of capital, and lowers risk diversification mechanisms that collectively elevate firm risk. Social Norms Theory (Hong & Kacperczyk, 2009) further reinforces this argument by demonstrating that firms perceived as environmentally irresponsible face lower institutional ownership, reduced analyst coverage, and higher stock price volatility. In Indonesia specifically, the combination of Perpres No. 98/2021, IDXCarbon, and POJK No. 51/2017 has created a regulatory environment in which carbon intensity increasingly functions as a priced risk factor for IDX-listed firms.

Meanwhile, AI innovation refers to the adoption and implementation of artificial intelligence-based technologies including machine learning, predictive analytics, and intelligent process automation in firms' business and operational processes (Li et al., 2021; Zhang et al., 2025). From the perspective of Resource-Based View Theory (Lockett & Thompson, 2009), firms that develop AI as a strategic capability are better positioned to manage environmental uncertainties, optimize resource use, and adapt to regulatory changes, thereby reducing both systematic and unsystematic risk. Empirically, AI adoption has been shown to improve emissions monitoring, operational efficiency, and sustainability reporting quality (Hudson & Morgan, 2024) while also reducing the information asymmetry that often underlies unsystematic risk (Qin J & Wang, 2025). However, AI adoption may simultaneously increase systematic risk by deepening firms' exposure to market-wide technological dynamics and digital infrastructure dependencies (Tian et al., 2024; Wu & Zhou, 2025), suggesting that its net effect on firm risk depends on the specific channel through which it operates.

The Effect of Carbon Intensity on Unsystematic Risk

Unsystematic risk refers to firm-specific volatility that is independent of broad market movements and can theoretically be diversified away through portfolio construction. However, when firms are exposed to carbon intensity defined as carbon emissions per unit of revenue, this form of risk may become non-trivial due to the idiosyncratic nature of each firm's regulatory exposure, carbon management capability, and stakeholder relationships (Bolton et al., 2021; Schuster et al., 2025).

Carbon intensity increases unsystematic risk through multiple channels. First, firms with high carbon exposure face greater uncertainty regarding future compliance costs under carbon pricing regimes, creating firm-specific cash flow volatility that investors price as idiosyncratic risk (Chen et al., 2025; Schuster et al., 2025). Second, firms that fail to manage carbon intensity effectively are more likely to face reputational damage, legal liability, and stakeholder pressure, all of which contribute to increased firm-specific uncertainty (Agustin et al, 2025; Q. Wang, 2023). Third, according to the neglect effect described in Social Norms Theory (Hong & Kacperczyk, 2009) investors tend to avoid firms with high carbon intensity because these firms are perceived as inconsistent with sustainability norms, leading to lower institutional ownership and greater stock price volatility.

Empirically, Arian & Sands, (2024) found that firms with high carbon emission levels experience increased unsystematic risk because investors perceive environmental and regulatory exposures as additional sources of firm-specific uncertainty. Huang et al., (2021) similarly found that the implementation of low-carbon city initiatives in China elevated unsystematic risk for exposed firms in the short term due to high compliance costs and policy uncertainty. Perera et al., (2023) further demonstrated that high carbon emission intensity is positively related to firm-specific volatility in the

United States. Jung et al., (2023) showed that carbon productivity, the ability to generate revenue per unit of carbon emissions, which is conceptually inverse to carbon intensity significantly reduces total and firm-specific volatility, confirming that carbon intensity acts as an amplifier of idiosyncratic risk. Choi et al., (2025) and Alsaifi et al., (2022) found that voluntary carbon disclosure reduces unsystematic risk by mitigating information asymmetry, further implying that carbon intensity in the absence of adequate disclosure is associated with elevated firm-specific uncertainty. Garcia-Jorcano et al., (2023) additionally documented that extreme sensitivity to carbon price changes elevates sectoral volatility, suggesting that carbon intensity functions as both a systematic and unsystematic risk factor. Based on this theoretical and empirical foundation, the following hypothesis is proposed:

H1: Carbon Intensity positively affects Unsystematic Risk.

The Effect of Carbon Intensity on Systematic Risk

Systematic risk represents market-wide, non-diversifiable risk that reflects a firm's co-movement with the broader market, typically captured through stock beta. Carbon intensity is theorized to elevate systematic risk because the financial consequences of carbon exposure including carbon pricing, regulatory tightening, and transition-related asset repricing are not firm-specific but rather affect entire markets and economies simultaneously, making them a systemic rather than idiosyncratic risk factor (Bolton et al., 2021; Sitompul et al., 2023).

From the perspective of Ethical Investing Theory (Heinkel et al., 2015) as green investors' portfolio exclusions of carbon-intensive firms become widespread, the resulting reduction in share demand and increase in cost of capital for carbon-exposed firms is transmitted across the market as a systematic factor. Schuster et al. (2025) demonstrated that carbon-related regulatory risks and investor surprises are priced as systematic risk components, as they affect broad sectoral and market returns rather than individual firm performance alone. Bolton et al., (2021) found that firms with high carbon emission levels carry higher carbon beta and are perceived as more sensitive to climate policy shocks, confirming that carbon intensity functions as a systematic risk factor in financial markets. Al-Fakir Al Rabab'a et al., (2024) documented that poor corporate carbon performance is negatively correlated with systematic risk measures across Asia-Pacific companies, meaning that firms with high carbon intensity face higher market sensitivity. Enders et al., (2025) further showed that carbon risk is embedded in equity pricing, with carbon-intensive stocks exhibiting higher exposure to systematic risk factors.

Monasterolo & Angelis, (2020) found that following the Paris Agreement, the systematic risk of carbon-intensive assets increased structurally, while low-carbon assets experienced declining market beta, providing direct evidence that global climate policy strengthens the carbon intensity–systematic risk transmission mechanism. Sitompul et al. (2023) reinforces this view by arguing that carbon intensity is non-diversifiable because it is embedded in macroeconomic structures and global policies, and should therefore be treated as a systematic risk factor equivalent to market beta. Finally, Döbbeling-Hildebrandt et al., (2024) showed that the implementation of carbon pricing policies has a significant and cross-country impact on market volatility, confirming that carbon intensity acts as a macro determinant of systematic risk. Based on this theoretical and empirical foundation, the following hypothesis is proposed:

H2: Carbon Intensity positively affects Systematic Risk.

The Moderating effect of AI Innovation

While carbon intensity is shown to elevate both systematic and unsystematic risk, firms are not passive recipients of these risk exposures. Firms that invest in AI innovation as reflected in AI-related patent activity develop strategic capabilities that may attenuate the adverse risk effects of carbon intensity (Li et al., 2021; Zhang et al., 2025). From the perspective of Resource-Based View Theory (Lockett & Thompson, 2009), AI innovation constitutes a rare and valuable firm-level resource that enables more efficient environmental management, superior carbon monitoring, and adaptive responses to regulatory changes, thereby reducing the uncertainty associated with carbon intensity.

Zhang et al. (2025) showed that AI adoption is associated with reduced systematic risk in firms with high environmental exposure, as AI capabilities allow firms to anticipate and manage carbon policy changes more effectively, smoothing their co-movement with market shocks. Li et al., (2021) demonstrated that AI innovation reduces idiosyncratic (unsystematic) risk by improving operational efficiency and strengthening firms' ability to manage sustainability-related uncertainties. Hudson & Morgan, (2024) found that firms with greater AI-related board exposure exhibit lower idiosyncratic

risk, consistent with the view that AI capabilities buffer firm-specific uncertainties. Luqman et al., (2024) showed that AI adoption supports corporate carbon neutrality efforts by enabling process optimization and intelligent environmental decision-making, thereby reducing the financial risk associated with carbon intensity. Zhou & Bu, (2025) demonstrated that AI adoption significantly reduces firm energy consumption through green innovation channels, helping firms respond more adaptively to environmental regulatory pressures and reducing both their operational uncertainty and market risk exposure. Wu & Zhou, (2025) found that AI innovation reduces carbon emission intensity at the firm level through a lifecycle efficiency perspective, suggesting that firms with stronger AI capabilities are better positioned to decouple revenue generation from carbon exposure. Yu (2025) further showed that AI applications in carbon trading markets improve risk management efficiency and market stability, indicating that AI-enabled firms benefit from reduced carbon risk volatility. Almaghrabi (2023) documented that environmental innovation and technological capabilities strengthen firms' resilience to climate risk, making their risk profiles more manageable in the face of carbon regulatory pressures.

However, it is important to note that AI innovation's moderating effect may differ across the two dimensions of firm risk. Based on the results of this study, AI innovation significantly weakens the positive effect of carbon intensity on unsystematic risk, as AI capabilities directly address the firm-specific sources of carbon-related uncertainty including compliance cost volatility, operational inefficiency, and information asymmetry that drive idiosyncratic risk. In contrast, the moderating effect of AI innovation on systematic risk is not statistically significant, suggesting that AI innovation at the firm level is insufficient to offset the macro-level, market-wide transmission of carbon intensity into systematic risk, which is driven by broader policy dynamics and investor sentiment beyond the control of individual firms. Based on this differentiated theoretical and empirical foundation, the following hypothesis is proposed:

H3: AI Innovation weakens the positive effect of Carbon Intensity on Firm Risk, particularly on Unsystematic Risk.

RESEARCH METHOD

Data and sample

This study employs a quantitative research design using secondary panel data obtained from publicly listed companies on the Indonesia Stock Exchange (IDX) over the period 2018–2024. Financial statement data and annual report data were sourced from the official IDX website (www.idx.co.id), while carbon emission data were obtained from companies' sustainability reports and annual reports as disclosed in their respective IDX filings. AI innovation data, proxied by the number of AI-related patents, were obtained from patent database records provided through academic sources. The study period ends in 2024 because sustainability reports and carbon emission disclosures for the majority of IDX-listed companies covering the fiscal year 2025 had not yet been published at the time of data collection, as Indonesian listed companies are generally required to publish their annual sustainability reports within four months following the fiscal year-end.

The sampling technique used is purposive sampling, in which sample members are selected based on specific criteria relevant to the research objectives. The criteria applied in this study are as follows:

1. Companies listed on the Indonesia Stock Exchange (IDX) that published annual reports and financial statements during the period 2018-2024.
2. Companies that have available carbon emission data for at least one year during the study period.
3. Companies that use the Indonesian Rupiah (IDR) as their reporting currency.
4. Companies that have complete stock price data sufficient for the estimation of systematic and unsystematic risk.

Table 1. Sample Selection Process

Criteria	Companies	Observations
IDX-listed companies with available carbon emission data (2018–2024)	74	518
Less: Observations for companies not yet listed as of 2018 (new listings joining after 2018)	-	(123)
Less: Observations with incomplete risk data	-	(1)
Final Sample	74	394

Source: Research Data, 2026

The final sample consists of 74 companies yielding 394 firm-year observations over the period 2018–2024, forming an unbalanced panel due to companies entering the sample at different points during the study period. The sample covers companies across 11 sectors, including Financial, Communication Services, Materials, Consumer Staples, Energy, Real Estate, Industrial, Consumer Discretionary, Information Technology, Health Care, and Utilities. The inclusion of financial sector companies in the sample is deliberate, as this study focuses on firm risk, both systematic and unsystematic, rather than on operational carbon performance alone; financial firms are equally exposed to carbon intensity risk through their investment portfolios, regulatory obligations, and market valuation dynamics. Similarly, the sample includes companies regardless of profitability status, as the exclusion of loss-making firms would introduce sample selection bias and reduce the generalizability of findings regarding the relationship between carbon intensity and firm risk.

Variable Measurement

Table 2. Operational Definition

Variable	Definition	Variable Measurement	Description	Source
Dependent Variable	Systematic Risk	Stock Beta (β)	Systematic risk is a non-diversifiable market risk driven by macroeconomic factors and overall market conditions.	Al-Kafir Al Rabab'a et al. (2024)
	Unsystematic Risk	Standard deviation of the regression residuals from the stock return	The unique risk of a company that is not related to market factors, measured from the variance of the regression error of returns against market factors (CAPM)	Ang et al. (2006); Ren et al. (2025)
Independent Variable	Carbon Intensity	CO_2 Emissions ÷ Firm Revenue	Risks arising from the company's exposure to carbon emission reduction policies, environmental regulations, and the transition to a low-carbon economy	Bolton et al. (2021); Chen et al. (2025)
Moderating Variable	AI Innovation	ln (1 + Number of AI Patents)	The level of adoption and implementation of artificial intelligence technology in business	Cockburn (2018)

			processes acts as a moderator that can strengthen or weaken the relationship between Carbon Intensity and Firm risk	
Control Variable	Return on Assets (ROA)	Net Profit After Taxes ÷ Total Assets	Return on Assets (ROA) measures how efficiently a company generates profit from its total assets. It reflects the firm's ability to convert assets into net income.	Singh (2024)
	Return on Equity (ROE)	Net Income ÷ Total Equity	Return on Equity (ROE) measures profitability relative to shareholders' equity, showing how effectively equity capital is used to generate profit.	Wet & Toit (2007)
	Firm Size	ln(Total Assets)	Firm size represents the scale of a company, commonly measured using the natural logarithm of total assets to reduce skewness.	Shalit & Sankar (2014)
	Market Capitalization	Stock Price × Number of Outstanding Shares	Market capitalization reflects the total market value of a company's outstanding shares and represents investor valuation of the firm.	Farooq et al. (2022)

Systematic Risk is measured using stock beta (β) of Capital Asset Pricing Model (CAPM), estimated from weekly stock return data regressed against the Indonesia Stock Exchange Composite Index (IHSG) return as the market benchmark. Weekly returns are computed from year-end closing prices. The market model used is: $R_{it} = \alpha + \beta_i R_{mt} + \varepsilon_{it}$. where R_{it} is the weekly return of firm i in year t and R_{mt} is the weekly return of the IHSG in year t. The resulting coefficient β_i represents the firm's systematic risk, capturing its sensitivity to market-wide movements (Al-Fakir Al Rabab'a et al., 2024). Unsystematic Risk is measured using the standard deviation of the residuals (ε_{it}) from the above market model regression, representing the component of stock return volatility that is unexplained by market movements and is therefore firm-specific (Ang et al., 2006; Ren et al., 2025). This measure is estimated annually for each firm-year observation. Carbon Intensity is measured as total CO_2 emissions divided by firm revenue (in tonnes per billion Rupiah), following Bolton et al., (2021) and Chen et al., (2025). This ratio captures the efficiency of a firm's revenue generation relative to its carbon emission footprint, with higher values indicating greater carbon exposure per unit of economic output. AI Innovation is proxied using the natural logarithm of one plus the number of AI-related patents held by the firm (ln (1 + number of AI patents)), following Cockburn, (2018). The logarithmic transformation is applied to reduce skewness in the patent count distribution. AI patent data were sourced from the Pangkalan Data Kekayaan Intelektual (PDKI) Indonesia, the official intellectual property database maintained by the Directorate General of Intellectual Property (DGIP) of the Republic of Indonesia. AI-related patents were identified using keyword searches covering terms such as 'artificial intelligence', 'machine learning', 'deep learning', and 'neural network', and were matched to IDX-listed companies based on applicant names cross-referenced with company identities disclosed in their annual reports.

Data Analysis Method

This study employs panel data regression analysis to examine the effect of carbon intensity on firm risk and the moderating role of AI innovation. Four regression models are estimated: two baseline models examining the direct effect of carbon intensity on systematic risk and unsystematic risk respectively, and two moderation models incorporating AI innovation and its interaction term with carbon intensity. The empirical model used is as follows:

$$\text{Systematic Risk} = \alpha + \beta1\ \text{Carbon Intensity} + \beta2\ \text{ROA} + \beta3\ \text{ROE} + \beta4\ \text{Firm Size} + \beta5\ \text{Market Cap} + \varepsilon$$

$$\text{Unsystematic Risk} = \alpha + \beta1\ \text{Carbon Intensity} + \beta2\ \text{ROA} + \beta3\ \text{ROE} + \beta4\ \text{Firm Size} + \beta5\ \text{Market Cap} + \varepsilon$$

$$\text{Systematic Risk} = \alpha + \beta1\ \text{Carbon Intensity} + \beta2\ \text{AI} + \beta3\ (\text{Carbon Intensity} \times \text{AI}) + \beta4\ \text{ROA} + \beta5\ \text{ROE} + \beta6\ \text{Firm Size} + \beta7\ \text{Market Cap} + \varepsilon$$

$$\text{Unsystematic Risk} = \alpha + \beta1\ \text{Carbon Intensity} + \beta2\ \text{AI} + \beta3\ (\text{Carbon Intensity} \times \text{AI}) + \beta4\ \text{ROA} + \beta5\ \text{ROE} + \beta6\ \text{Firm Size} + \beta7\ \text{Market Cap} + \varepsilon$$

All models are estimated using Ordinary Least Squares (OLS) regression with year fixed effects (i.Year in Stata), which controls for time-specific shocks common to all firms in a given year, such as macroeconomic conditions, regulatory changes, and market-wide carbon policy developments. Year fixed effects are implemented by including year dummy variables directly in the OLS specification. This approach is appropriate for an unbalanced panel where the primary source of variation of interest is cross-sectional heterogeneity across firms in carbon intensity and AI innovation, rather than within-firm time variation. Standard errors are estimated at the firm-year level. All statistical analyses are conducted using Stata software.

RESULT

Descriptive Statistics

Table 3. Descriptive Statistics

	Mean	Median	Minimum	Maximum
CARBON INTENSITY	6425.322	555.958	48.884	116258.583
SYSTEMATICRISK	0.882	0.832	-0.691	3.133
UNSYSTEMATICRISK	0.048	0.045	0.014	0.112
AIINNOVATION	1.371	0.693	0.000	5.204
ROA	0.066	0.046	-0.067	0.344
ROE	0.170	0.129	-0.264	1.429
FIRMSIZE	22.115	21.860	19.195	25.650
MARKETCAP	5.755e+09	2.296e+09	61141305.151	5.885e+10

Source: Research Data, 2026

Descriptive statistics are used to provide an overview of the characteristics of the variables used in this study. Table 3 presents the descriptive statistics for 394 firm-year observations across 74 IDX-listed companies over the period 2018–2024.

Carbon Intensity shows a mean of 6,425.322 with a wide range (48.884–116,258.583), indicating substantial heterogeneity in carbon exposure across the sample. Systematic Risk averages 0.882, slightly below the market beta of 1.0, while Unsystematic Risk averages 0.048, reflecting relatively modest firm-specific volatility on average. AI Innovation has a mean of 1.371 with a minimum of 0.000, suggesting that many firms in the sample have not yet engaged in AI patent activity. For the control variables, ROA and ROE average 0.066 and 0.170 respectively, with negative minimum values confirming the inclusion of loss-making firm-year observations in the sample. Firm Size and

Market Capitalization reflect the wide range of firm scales represented across the 11 sectors in the sample.

Correlation Analysis

Table 4. Pearson Correlation Matrix

	CARBONINTENSITY	SYSTEMATICRISK	UNSYSTEMATICRISK	AIINNOVATION	ROA	ROE	FIRMSIZE	MARKETCAP
CARBONINTENSITY	1.000							
SYSTEMATICRISK	0.080	1.000						
	(0.114)							
UNSYSTEMATICRISK	0.177***	0.211***	1.000					
	(0.000)	(0.000)						
AIINNOVATION	0.181***	-0.044	-0.080	1.000				
	(0.000)	(0.384)	(0.113)					
ROA	0.029	-0.226***	0.000	0.080	1.000			
	(0.557)	(0.000)	(0.996)	(0.112)				
ROE	0.092*	0.079	-0.287***	0.183***	-0.338***	-0.175***	1.000	
	(0.049)	(0.001)	(0.683)	(0.011)	(0.000)			
FIRMSIZE	0.092*	0.079	-0.287***	0.183***	-0.338***	-0.175***	1.000	
	(0.067)	(0.118)	(0.000)	(0.000)	(0.000)	(0.000)		
MARKETCAP	-0.025	-0.043	-0.324***	0.204***	0.048	0.121**	0.600***	1.000
	(0.615)	(0.390)	(0.000)	(0.000)	(0.341)	(0.016)	(0.000)	

p-values in parentheses
*p<0.1, **p<0.05, ***p<0.01

Source: Research Data, 2026

Regression Analysis

Table 5. Hypothesis Testing Results

	(1) Systematicrisk	(2) Unsystematicrisk	(3) Systematicrisk	(4) Unsystematicrisk
Carbon Intensity	0.048***	0.001**	0.054***	0.002***
	(3.18)	(2.19)	(2.67)	(2.64)
ROA	-1.224*	-0.006	-1.216*	-0.006
	(-1.73)	(-0.34)	(-1.74)	(-0.34)
ROE	-0.048	0.002	-0.052	0.001
	(-0.25)	(0.48)	(-0.28)	(0.26)
Firmsize	0.057*	-0.002**	0.061*	-0.002*
	(1.78)	(-2.04)	(1.82)	(-1.88)
logMarketCap	-0.118***	-0.004***	-0.117***	-0.004***
	(-3.48)	(-3.37)	(-3.43)	(-3.42)
AIINNOVATION			0.038	0.005**
			(0.64)	(2.03)
Carbon Intensity*AI			-0.006	-0.001**
			(-0.66)	(-2.01)
_cons	1.503***	0.191***	1.377***	0.182***

	(3.43)	(12.39)	(2.71)	(10.59)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
r2	0.509	0.221	0.509	0.229
r2_a	0.495	0.198	0.492	0.203
N	394	394	394	394

Source: Research Data, 2026

Table 5 presents the results of the panel data regression analysis with year fixed effects. Four models are estimated: Models 1 and 2 examine the direct effect of Carbon Intensity on Systematic Risk and Unsystematic Risk respectively, while Models 3 and 4 incorporate AI Innovation and its interaction term with Carbon Intensity to test the moderating hypothesis.

Carbon Intensity has a positive and significant effect on Unsystematic Risk at the 5 percent significance level in Model 2, indicating that firms with higher carbon intensity experience greater firm-specific return volatility. This result is confirmed in Model 4, where the coefficient remains positive and significant at the 1% level after the inclusion of AI Innovation and the interaction term. H1 is therefore supported. Carbon Intensity also has a positive and significant effect on Systematic Risk at the 1 percent significance level in Model 1, indicating that firms with higher carbon exposure face greater sensitivity to market-wide movements. This result is confirmed in Model 3, where the coefficient remains positive and significant at the 1 percent level. H2 is therefore supported.

Regarding the moderating role of AI Innovation, the results differ between the two dimensions of firm risk. The interaction term between Carbon Intensity and AI Innovation on Systematic Risk in Model 3 is negative but not statistically significant, indicating that AI Innovation does not significantly attenuate the relationship between Carbon Intensity and Systematic Risk. In Model 4, however, the interaction term on Unsystematic Risk is negative and significant at the 5 percent level, indicating that firms with higher levels of AI Innovation are able to reduce the positive effect of Carbon Intensity on Unsystematic Risk. H3 is therefore partially supported: AI Innovation significantly weakens the effect of Carbon Intensity on Unsystematic Risk, but not on Systematic Risk. This differential finding is theoretically consistent, as AI innovation operates primarily at the firm level through improved operational efficiency, environmental monitoring, and carbon management, which directly addresses firm-specific sources of unsystematic risk, whereas systematic risk is driven by macro-level forces such as carbon pricing policies and market-wide regulatory shifts that are beyond the capacity of individual firm-level AI capabilities to offset.

For the control variables, Market Capitalization is consistently negative and significant at the 1 percent level across all models, confirming that larger market-valued firms exhibit lower systematic and unsystematic risk. Firm Size shows a positive and significant effect on Systematic Risk at the 10 percent level but a negative and significant effect on Unsystematic Risk at the 5 percent level, suggesting that while larger firms by assets are more exposed to market movements, they benefit from reduced firm-specific volatility. ROA is negatively significant for Systematic Risk at the 10 percent level in Models 1 and 3, consistent with the view that more profitable firms face lower market sensitivity.

Table 6. Hypothesis Testing Results

Hypothesis	Description	Result
H1	Carbon Intensity positively affects Unsystematic Risk	Supported ($\beta = 0.001$, $p < 0.05$)
H2	Carbon Intensity positively affects Systematic Risk	Supported ($\beta = 0.048$, $p < 0.01$)
H3a	AI Innovation weakens the effect of Carbon Intensity on Systematic Risk	Not Supported ($\beta = -0.006$, $p > 0.10$)
H3b	AI Innovation weakens the effect of Carbon Intensity on Unsystematic Risk	Supported ($\beta = -0.001$, $p < 0.05$)

Source: Research Data, 2026

DISCUSSION

The finding that carbon intensity positively and significantly affects unsystematic risk supports H1 and is consistent with the argument that high carbon exposure creates firm-specific uncertainty through multiple channels, including rising compliance costs, reputational pressures, and investor avoidance behavior. In practical terms, firms with high carbon intensity face greater volatility in their cash flows and earnings prospects as environmental regulations tighten particularly under Indonesia's carbon pricing framework established through Perpres No. 98/2021 and the operationalization of IDXCarbon in 2023. This increases the unpredictability of firm-specific performance, which investors interpret as elevated idiosyncratic risk. Companies are therefore advised to proactively reduce their carbon emission intensity, not merely as an environmental obligation, but as a concrete financial risk management strategy that stabilizes firm-specific return volatility. This result is supported by Arian & Sands (2024), who found that firms with high carbon emission levels experience increased unsystematic risk as investors perceive environmental regulatory exposure as an additional source of firm-specific uncertainty. Perera et al., (2023) similarly documented a positive relationship between carbon emission intensity and firm-specific volatility in the United States. Choi et al., (2025) further showed that carbon disclosure reduces unsystematic risk by mitigating information asymmetry, implying that firms which fail to manage and disclose their carbon intensity face compounding idiosyncratic risk. In contrast, Jung et al., (2023) found that carbon productivity the inverse of carbon intensity significantly reduces firm-specific volatility, reinforcing the view that carbon efficiency is valued by the market as a signal of firm stability. However, Ozkan et al., (2023) found that the relationship between carbon-related risk and firm risk is highly context-dependent, moderated by institutional quality and governance characteristics, suggesting that the magnitude of this effect may vary across industries and firm types within the Indonesian context.

The finding that carbon intensity positively and significantly affects systematic risk supports H2 and reflects the macro-level, non-diversifiable nature of carbon transition risk. Unlike unsystematic risk, which is firm-specific, systematic risk captures firms' co-movement with broad market dynamics and carbon intensity amplifies this co-movement because the financial consequences of carbon regulation, such as carbon pricing and energy transition policies, affect the entire market simultaneously rather than individual firms in isolation. For firms and investors, this implies that carbon intensity is not merely a firm-level concern but a market-wide risk factor that cannot be eliminated through portfolio diversification. Investors should therefore incorporate carbon intensity as a systematic risk factor in asset pricing and portfolio construction, demanding appropriate risk premiums for carbon-intensive holdings. This result is consistent with Bolton et al., (2021), who demonstrated that firms with high carbon emission levels carry higher carbon beta and are perceived by investors as a new source of systematic risk due to transition risks toward a low-carbon economy. Monasterolo & Angelis, (2020) further found that following the Paris Agreement, the systematic risk of carbon-intensive assets increased structurally, while low-carbon assets experienced declining market beta, confirming that global climate policy strengthens the transmission of carbon intensity into systematic risk. Enders et al., (2025) also showed that carbon risk is embedded in equity pricing, with carbon-intensive stocks exhibiting higher exposure to systematic risk factors. Conversely, Al-Fakir Al Rabab'a et al., (2024) found that the relationship between carbon performance and systematic risk varies across Asia-Pacific countries depending on regulatory environments and investor awareness, suggesting that the strength of this relationship in Indonesia may evolve as carbon market institutions mature. Schuster et al. (2025) similarly noted that carbon-related risks translate into systematic risk primarily through investor surprises unexpected regulatory changes or emissions disclosures highlighting the importance of consistent and transparent carbon reporting in stabilizing market perceptions of firm risk.

The finding that AI innovation significantly weakens the positive effect of carbon intensity on unsystematic risk, but not on systematic risk, provides partial support for H3 and represents the most nuanced contribution of this study. The significant moderation on unsystematic risk indicates that firms with stronger AI capabilities are better equipped to manage the firm-specific consequences of carbon intensity including operational inefficiencies, compliance cost volatility, and information asymmetry thereby stabilizing their idiosyncratic risk profiles. Practically, this suggests that investment in AI-based capabilities, such as intelligent energy management systems, real-time emissions monitoring, and AI-driven sustainability reporting, constitutes a financially meaningful risk mitigation strategy for carbon-exposed firms in Indonesia. Li et al., (2021) support this finding by demonstrating that AI innovation

reduces idiosyncratic risk through improved operational efficiency and firms' capacity to manage sustainability-related uncertainties. Hudson & Morgan, (2024) similarly found that firms with greater AI exposure exhibit lower firm-specific risk, consistent with the view that AI capabilities buffer idiosyncratic uncertainty. Zhou & Bu, (2025) further showed that AI adoption reduces firm energy consumption through green innovation channels, helping firms respond more adaptively to environmental regulatory pressures. Luqman et al., (2024) also documented that AI supports corporate carbon neutrality by enabling process optimization and intelligent environmental decision-making, thereby reducing the financial uncertainty associated with carbon exposure. The absence of a significant moderating effect on systematic risk, however, is equally important to acknowledge. Zhang et al. (2025) noted that while AI adoption reduces firm-level environmental uncertainties, it does not insulate firms from market-wide carbon policy shocks, which are determined by macroeconomic and regulatory dynamics that no individual firm can control through technological investment alone. Tian et al. (2024) further cautioned that AI adoption may itself introduce new dimensions of systematic risk by deepening firms' integration with market-wide digital infrastructure dynamics, partially offsetting its risk-reducing benefits at the macro level. These contrasting effects explain why AI innovation's moderating influence is confined to unsystematic risk in the Indonesian context, where carbon market institutions are still developing and macro-level carbon risk pricing remains the dominant systematic force.

CONCLUSION

This study examines the effect of carbon intensity on systematic risk and unsystematic risk among companies listed on the Indonesia Stock Exchange over the period 2018–2024, as well as the moderating role of AI innovation in this relationship. The results show that carbon intensity has a positive and significant effect on both unsystematic risk and systematic risk, indicating that firms with higher carbon exposure face greater firm-specific volatility as well as heightened sensitivity to market-wide movements. These findings confirm that carbon intensity functions as a dual risk factor operating simultaneously at the firm-specific and market-wide levels. Furthermore, AI innovation significantly weakens the positive effect of carbon intensity on unsystematic risk, suggesting that firms with stronger AI capabilities are better positioned to manage the firm-specific consequences of carbon exposure. However, AI innovation does not significantly moderate the relationship between carbon intensity and systematic risk, indicating that macro-level carbon transition risks remain beyond the reach of individual firm-level technological capabilities. This study contributes to the literature by providing empirical evidence from an emerging market setting and by demonstrating that AI innovation plays a differentiated moderating role across the two dimensions of firm risk, highlighting the importance of distinguishing between systematic and unsystematic risk when examining the financial implications of carbon intensity.

PRACTICAL SUGGESTIONS

Based on the findings of this study, several practical recommendations are offered for key stakeholders. For companies, particularly those operating in carbon-intensive sectors, it is recommended to integrate AI-based technologies such as intelligent energy management systems, real-time emissions monitoring platforms, and AI-driven sustainability reporting tools into their operational and risk management frameworks. Reducing carbon intensity should be treated not merely as a compliance obligation but as a proactive financial risk management strategy, given its demonstrated effect on both firm-specific and market-wide risk profiles. Companies with limited AI capabilities are encouraged to prioritize incremental AI adoption in areas most directly linked to carbon management, such as supply chain optimization and energy efficiency monitoring, as these represent the most direct pathways through which AI innovation mitigates unsystematic risk.

For investors, the findings suggest that carbon intensity should be incorporated as an explicit risk factor in asset pricing models and portfolio construction, as it contributes to both systematic and unsystematic risk dimensions. Carbon-intensive holdings warrant higher risk premiums, and portfolio managers should actively monitor firms' AI innovation capabilities as a moderating factor in assessing the net carbon risk exposure of their portfolios. For policymakers and regulators, the results underscore the importance of maintaining consistent and transparent carbon pricing frameworks such as those established through Perpres No. 98/2021 and IDXCarbon as these regulatory signals are key drivers of how carbon intensity is priced into systematic risk across the market. Supporting AI adoption incentives,

particularly for small and medium-sized listed firms with limited technological resources, could also help reduce the broader market-wide financial risks associated with Indonesia's carbon transition.

THEORETICAL SUGGESTIONS

This study opens several directions for future research. First, future studies are encouraged to employ broader and more granular measures of AI innovation beyond patent counts, such as AI investment expenditure, AI talent density, or firm-level AI adoption indices, to more comprehensively capture the depth and breadth of firms' AI capabilities and their risk management implications. Second, the observation period of this study is constrained by carbon emission data availability up to 2024; as sustainability disclosures for fiscal year 2025 were not yet publicly available at the time of data collection, future research should extend the study period to capture the longer-term dynamics of carbon intensity and firm risk in Indonesia's evolving carbon market. Third, future studies could incorporate corporate governance variables such as board composition, ESG committee presence, and institutional ownership as additional moderating or mediating factors, given the well-established role of governance quality in shaping firms' environmental risk management effectiveness. Fourth, cross-country comparative studies within the ASEAN region would be valuable in examining whether the differentiated moderating effect of AI innovation on systematic versus unsystematic risk is unique to Indonesia's institutional context or generalizable across emerging markets with varying carbon regulatory environments. Finally, future research could explore non-linear or threshold effects in the carbon intensity–firm risk relationship, as the highly skewed distribution of carbon intensity in this sample suggests that the financial risk implications may intensify disproportionately beyond certain emission thresholds.

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