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RESEARCH ARTICLE

Research on the impact of environmental risk factors on pricing efficiency in China's stock market

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ABSTRACT

This study examines the impact of environmental risk factors on market pricing efficiency in China's stock market from 2018 to 2024. Using a comprehensive panel dataset of 2,486 listed companies, the research constructs a multidimensional environmental risk index incorporating both physical and transition risks. The empirical analysis reveals that environmental risks significantly impair market efficiency through direct operational impacts and indirect investor perception channels. A one-standard-deviation increase in environmental risk leads to a 0.186-standard-deviation decrease in price synchronicity and a 0.224-standard-deviation increase in price delay. The investor risk perception channel accounts for approximately 35% of the total effect. Cross-sectional analysis shows that environmental risk effects are 1.5 times stronger in high-pollution industries compared to low-pollution sectors. These relationships remain robust after addressing endogeneity concerns through instrumental variable estimation and various robustness tests. The findings contribute to the growing literature on environmental finance and have important implications for improving environmental risk disclosure frameworks and market efficiency in emerging economies.

Keywords: environmental risk factors; market pricing efficiency; investor risk perception; Chinese stock market; behavioral finance

1. Introduction

1.1. Research background and significance

Environmental risk factors have played a growing role in financial markets with deepening global environmental concerns. In China, with the development of ecological civilization and green development, environmental policies have become stricter, and requirements for environmental disclosures have become more stringent, having a profound impact on capital markets. Empirical studies have confirmed that environmental risk has become an important driver of firm value and investors' decision-making[1]. This is particularly worth studying in emerging economies such as China.

The mechanism for environmental risk having an impact on pricing efficiency in stocks can manifest in two forms: directly impacting firms' operational expenses, reputation, and future outlook, and indirectly impacting market pricing efficiency through investors' perception of and behavior in relation to risk[2].

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Recent studies have determined that investment decisions increasingly prioritize environmental factors in regard to risk[3], and increased transparency in the environment can profoundly impact investors' perception of risk[4].

The mechanism of impact for environmental risk in China's market environment is exhibited distinctly. Empirical studies regarding China's high-pollution companies have determined that environmental policy shifts have a significant impact on stock market responses[5]. In addition, environmental factors such as atmospheric environment have been shown to have an impact on investors' trading behavior[6]. All of these have emphasized and necessitated studying the impact mechanism for environmental factors regarding risk on pricing efficiency in China's stock market.

1.2. Research objectives and innovation

This study aims to systematically examine the impact of environmental risk factors on pricing efficiency in China's stock market. Specifically, it attempts to construct a comprehensive environmental risk assessment framework to explore the mechanisms through which environmental risk affects market pricing efficiency via direct impacts and the mediating effect of investor risk perception. This research not only helps deepen theoretical understanding of the relationship between environmental risk and market efficiency but also provides empirical evidence for investor decision-making and policy formulation.

The innovation of this research is manifested in several aspects. First, theoretically, this study organically integrates environmental risk theory, market efficiency theory, and investor risk perception theory to construct a more complete analytical framework. Second, methodologically, this study employs a multidimensional environmental risk indicator system, considering not only traditional environmental performance indicators but also incorporating dynamic factors such as investor sentiment and market reactions. Finally, in empirical analysis, this study fully considers the uniqueness of the Chinese market, conducting detailed heterogeneity analysis across different industries and investor types, providing more targeted research findings.

This study extends existing literature by addressing important gaps in environmental finance research. While prior studies such as Hong et al.[7] have established general relationships between climate risks and market efficiency, this research advances understanding by explicitly modeling and empirically testing the mediating role of investor risk perception—a critical transmission mechanism largely overlooked in previous studies. The mediation approach quantifies the relative importance of direct operational impacts versus indirect perception-based channels. Additionally, the cross-industry comparative analysis moves beyond homogeneous treatment of firms by examining how regulatory intensity and pollution characteristics moderate environmental risk effects, revealing important variations in impact mechanisms across different market segments and contributing to a more contextualized understanding of environmental risk transmission.

This research's development enriches academic literature in environmental finance and provides important policy implications for improving environmental information disclosure systems and market pricing efficiency. Meanwhile, the research results offer valuable references for investor decision-making in the context of environmental risk. Under China's broader context of promoting green finance development and ecological civilization construction, this study holds significant theoretical value and practical implications.

2. Theoretical framework and literature review

2.1. Basic theories

2.1.1. Environmental risk theory

Environmental risk theory deals with uncertainty and potential impact in relation to environment factors in companies' operations. Environmental risks can be broadly differentiated between transition and physical risks[7]. Physical risks involve direct consequences of extreme weather and natural catastrophes for companies' assets and operations[8]. Transition risks involve indirect consequences of environmental policy changes, technology, and changes in market demand[9]. These aspects affect companies' value through an impact on cash flows, assets, and operational expenses[10]. The distinction between these risk categories is particularly significant in the Chinese context, where a unique economic development model combines rapid industrialization with ambitious environmental policies, creating a dynamic interplay between physical environmental impacts and policy-driven transitions. Unlike developed markets where transition risks often dominate due to established regulatory frameworks, China's environmental risk landscape presents a notable interaction between substantial physical risks (stemming from industrial concentration and geographical vulnerability to climate events) and accelerating transition risks (driven by recent policy shifts toward ecological civilization). Separately quantifying these risk dimensions in the Chinese market context offers valuable insights into how different types of environmental risks might influence market efficiency, complementing existing research that has often employed aggregated environmental risk measures or focused primarily on developed market contexts.

2.1.2. Market pricing efficiency theory

Market pricing efficiency theory deals with quickness and accuracy with which information enters in market prices. Efficient market theory holds that information regarding environment-related risks must enter into stock prices at once and accurately[7]. Due to complexity and long-term availability, information about environment-related risks, markets will most of the times exhibit biases[11]. This is most evidently seen in emerging economies, with poor information quality in environments and lack of awareness among investors, further decreasing pricing efficiency in markets[1].

2.1.3. Investor risk perception theory

Investor risk perception theory deals with whom, when, and with whom investors perceive and respond in relation to several types of risks. Research identifies that investors' perception regarding risks is guided through cognitive biases, emotion, and external information[12]. Recent studies conclude that investors' feelings have a significant role to play in financial markets, particularly regarding environment-related issue[13]. In case of environment-related risks, investors' perception regarding risks plays an important role in investment and, subsequently, pricing efficiency in markets[14].

2.2. Literature review

2.2.1. Environmental risk and market pricing efficiency

Interrelationships between environment-related risk and effective pricing in markets have been examined in detail recently regarding studies. Institutional investors' survey reveals climate risks have become important drivers in terms of consideration in investment, most of them being regulatory and physical in nature[3]. Other studies reveal that companies with greater environment-related risk exposure have heightened tail risk, underpriced in the marketplace[9]. Empirical studies reveal strong, significant, and negative interrelationship between perceived climate risk and stocks' price[2]. In a Chinese marketplace, studies confirm environment policy changes have significant impact on reaction in the stock marketplace in high-pollution companies[5]. "Pollution premium" is revealed through studies, with high-pollution companies having to pay a premium on stocks for compensating investors for taking environment-related risks[11]. Time-series analysis reveals strong spillovers between carbon, fossil fuels, and clean-energy markets, proposing intertwined relations in environment-related pricing[15]. Other studies report climate change news risk having significant impact on corporation bond return, and environment-related risks having impact on a range of assets[16]. All these studies are supported through studies reporting impact of climate-related risks regarding determination of effective pricing on a range of market environments[8].

2.2.2. Research on investor risk perception

Research on investor risk perception has evolved significantly in recent years. Studies find that enhanced environmental information transparency significantly influences investor risk perception and firms' cost of equity [4]. Environmental factors such as air quality demonstrate measurable effects on investor trading behavior in the Chinese market [6]. Empirical evidence shows that shareholder activism can promote voluntary disclosure of climate risks, improving investors' ability to assess environmental risks[17]. Recent studies reveal that investors exhibit different sensitivities to climate-related transition and physical risks, reflected in asset pricing[14]. Early research provides foundational evidence that environmental performance information impacts stock market valuations[18], while newer studies explore the relationship between environmental risks and stock price crash risk[1].

2.2.3. Literature Summary

The literature review reveals several key trends in environmental risk and market efficiency research. Studies increasingly combine environmental finance, behavioral finance, and market efficiency theories. Methodological innovations incorporate sophisticated quantitative methods and behavioral factors. Market-specific findings suggest varying impacts across different market contexts and investor types.

Current research gaps include limited investigation of transmission mechanisms between environmental risk and market efficiency, insufficient attention to the mediating role of investor risk perception, and the need for more comprehensive empirical evidence from emerging markets. These gaps provide opportunities for further research contribution.

2.3. Research framework and hypotheses

Based on the theoretical analysis and literature review, the following hypotheses are formulated:

H1: Environmental risk significantly impacts market pricing efficiency

H1a: Physical environmental risk negatively correlates with market pricing efficiency

H1b: Transition environmental risk negatively correlates with market pricing efficiency

H2: Investor risk perception mediates the impact of environmental risk on market pricing efficiency

H2a: Environmental risk positively affects investor risk perception

H2b: Investor risk perception negatively affects market pricing efficiency

H3: Industry characteristics moderate the relationship between environmental risk and market pricing efficiency

H3a: Environmental risk has a stronger impact on market pricing efficiency in high-pollution industries

H3b: The mediating effect of investor risk perception is more significant in environmentally sensitive industries

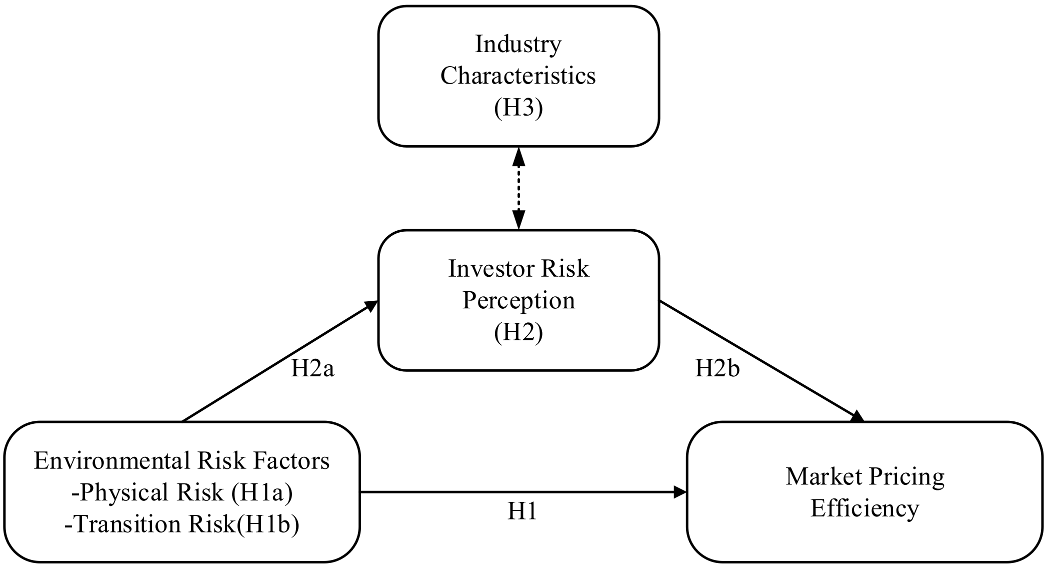

Figure 1. Theoretical research framework.

This research framework demonstrates several innovations. It decomposes environmental risk effects into direct and indirect pathways, incorporates investor risk perception as a mediating variable, and considers industry characteristics' moderating effects. The framework integrates behavioral finance perspectives with traditional market efficiency theory, addressing identified research gaps through a comprehensive analytical approach. Recent empirical evidence supports the proposed relationships, while theoretical foundations strengthen the framework's conceptual basis[19,20].

3. Research design

3.1. Sample selection and data sources

This study examines A-share companies listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange from January 1, 2018, to December 31, 2024. The sample selection process follows Xu et al.[1] and Yu et al.[4], excluding financial institutions due to their unique regulatory environment, ST and *ST companies experiencing financial distress, companies undergoing major asset restructuring, and those with severe data missing. The final balanced panel dataset comprises 2,486 listed companies with 14,916 firm-year observations.

The environmental information data is sourced from multiple authoritative databases. Following Teng and He[6], corporate environmental disclosure data is collected from annual reports and corporate social responsibility reports through Wind Database. Air pollutant emission data is obtained from provincial and municipal ecological environment bureaus' public records, consistent with the approach of Guo et al.[5]. Carbon emission data is collected from China's carbon trading exchanges. Stock market trading data and corporate financial information are extracted from Wind and CSMAR databases. Macroeconomic data comes from the National Bureau of Statistics and the People's Bank of China. The sample period extends through 2024 to capture recent environmental policy developments and market responses, with data collected up to September 30, 2024.

3.2. Variable definition and measurement

3.2.1. Environmental risk factor construction

Building on Ilhan et al.[9] and Zhang[14], this study constructs a comprehensive environmental risk evaluation system encompassing both physical and transition risks.

Physical risks capture immediate environmental impacts through extreme weather events, natural disasters, and pollution levels. Transition risks reflect longer-term structural changes in regulatory environment, technological innovation, and market preferences. As shown in **Table 1**, the measurement framework incorporates six key dimensions.

Table 1. Environmental risk factor measurement framework.

Risk Category	Dimension	Indicator	Measurement Method	Data Source
Physical Risk	Extreme Weather	Weather Event Frequency (WEF)	Natural logarithm of annual extreme weather events affecting company operations	Weather bureau records
	Natural Disaster	Disaster Loss Ratio (DLR)	Annual disaster-related economic losses / Total assets	Company disclosures
	Environmental Pollution	Emission Intensity (EI)	Weighted sum of major pollutant emissions / Operating revenue	Environmental reports
Transition Risk	Policy Pressure	Environmental Regulation Index (ERI)	Environmental protection expenditure / Operating revenue	Annual reports
	Technology Innovation	Green R&D Intensity (GRI)	Environmental technology R&D investment / Operating revenue	Annual reports
	Market Preference	ESG Rating Change (ERC)	Annual change in third-party ESG ratings	Rating agencies

The Environmental Risk Index (ERI) construction follows the methodology of Krueger et al.[3], employing standardization and entropy-weighted aggregation. Each indicator is first standardized using min-max normalization, then weighted based on empirical importance and aggregated into the final index. The weighting scheme reflects both academic literature findings and market practitioner perspectives on relative risk importance.

3.2.2. Market pricing efficiency indicators

To comprehensively assess market pricing efficiency, this study employ three complementary measures detailed in **Table 2**. For price synchronicity (SYNCH), the market model regression is specified as:

$$R_{i,t} = \alpha_i + \beta_{1i} R_{m,t} + \beta_{2i} R_{ind,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the weekly return of stock i, $R_{m,t}$ is the market return, and $R_{ind,t}$ is the industry return. The R^2 from this regression is then transformed using the logistic transformation shown in **Table 2** to obtain SYNCH.

The price delay measure (DELAY) is estimated through a regression incorporating lagged market returns:

$$R_{i,t} = \alpha_i + \beta_{0i} R_{m,t} + \sum_{n=1}^{5} \beta_{ni} R_{m,t-n} + \varepsilon_{i,t} \tag{2}$$

where $R_{m,t-n}$ represents market returns with lags up to five days. The DELAY measure captures how quickly stock prices adjust to market-wide information.

For the pricing error (MAPE), P_t represents the actual stock price and V_t represents the theoretical value estimated using a fundamental valuation model that incorporates both financial and environmental risk factors. The absolute percentage difference between these values is averaged over the measurement period to obtain the final MAPE measure. As shown in **Table 2**, these measures collectively capture different dimensions of market efficiency including information incorporation speed and pricing accuracy.

Table 2. Market pricing efficiency measurement framework.

Indicator	Symbol	Calculation Method	Definition	Source Research
Price Synchronicity	SYNCH	$\mathrm{SYNCH}_{i,t} = \ln\left(\frac{R^2}{1-R^2}\right)$ from market model regression	Measures co-movement between individual stock returns and market/industry returns	Hong et al. [8]
Price Delay	DELAY	Computed from: $R_{i,t} = \alpha_i + \beta_{0i}R_{m,t} + \sum_{n=1}^{5}\beta_{ni}R_{m,t-n} + \varepsilon_{i,t}$	Captures the speed of price adjustment to market-wide information	Xu et al. [1]
Pricing Error	MAPE	$\mathrm{MAPE}i,t = \frac{1}{T}\sum t = 1^T \left\|\frac{P_t - V_t}{V_t}\right\|$	Measures deviation between actual price and theoretical value	Ben Ameur et al. [2]

3.2.3. Control variables

The selection of control variables follows Ben Ameur et al.[2] and Yu et al.[4], incorporating firm characteristics, ownership structure, and market factors. These include firm size (SIZE), leverage (LEV), profitability (ROA), growth potential (GROWTH), institutional ownership (INST), ownership concentration (TOP1), analyst coverage (ANALYST), trading volume (TURN), and stock volatility (VOL). All financial variables are winsorized at the 1st and 99th percentiles to mitigate outlier effects.

3.3. Model specification

Building on prior literature in environmental finance and market efficiency[1,2], this study develops a comprehensive econometric framework to examine the relationship between environmental risk factors and market pricing efficiency. Following Hong et al.[8] and Ben Ameur et al.[2], the baseline model tests the direct effect of environmental risk on market pricing efficiency:

$$\mathrm{EFF}i,t = \beta_0 + \beta_1\mathrm{ERI}i,t + \sum_{k=1}^{K}\beta_{k+1}\mathrm{Controls}k,i,t + \sum\mathrm{Year} + \sum\mathrm{Ind} + \varepsilon i,t \tag{3}$$

where $\mathrm{EFF}i,t$ represents the market pricing efficiency measures (SYNCH, DELAY, or MAPE) for firm i in year t, $\mathrm{ERI}i,t$ is the environmental risk index, and $\mathrm{Controls}_{k,i,t}$ represents the set of control variables.

To investigate the mediating role of investor risk perception, consistent with Yu et al.[4] and Zhang[14], a mediation analysis framework is employed:

$$\mathrm{RISK}i,t = \alpha_0 + \alpha_1\mathrm{ERI}i,t + \sum_{k=1}^{K}\alpha_{k+1}\mathrm{Controls}k,i,t + \sum\mathrm{Year} + \sum\mathrm{Ind} + \mu i,t \tag{4}$$

$$\mathrm{EFF}i,t = \gamma_0 + \gamma_1 \mathrm{ERI}i,t + \gamma_2 \mathrm{RISK}i,t + \sum k = 1^K \gamma_{k+2} \mathrm{Controls}k,i,t + \sum \mathrm{Year} + \sum \mathrm{Ind} + \nu i,t \tag{5}$$

where $\mathrm{RISK}_{i,t}$ captures investor risk perception through a composite index. This investor risk perception measure incorporates three main components: (1) Market Sentiment Indicators, including Environmental News Sentiment derived from news databases and Environmental Social Media Index capturing online discussions; (2) Risk Premium Measures, including Environmental Beta measuring stock return sensitivity to environmental news and Green Premium/Discount comparing actual P/E ratios to industry averages; and (3) Trading Behavior Metrics, capturing institutional ownership changes following environmental events and abnormal trading patterns around environmental announcements. These components are standardized, weighted using principal component analysis (with the first principal component typically explaining approximately 65% of variance), and aggregated to form the comprehensive RISK index. Higher values indicate stronger investor perception of environmental risks.

Following Guo et al.[5] and Hsu et al.[11], the moderating effect of industry characteristics is examined using:

$$\mathrm{EFF}i,t = \delta_0 + \delta_1 \mathrm{ERI}i,t + \delta_2 \mathrm{IND}i,t + \delta_3 \left(\mathrm{ERI}i,t \times \mathrm{IND}i,t\right) + \sum k = 1^K \delta_{k+3} \mathrm{Controls}k,i,t + \sum \mathrm{Year} + \sum \mathrm{Ind} + \omega i,t \tag{6}$$

where $\mathrm{IND}_{i,t}$ represents industry characteristics, primarily focusing on pollution intensity and environmental sensitivity measures.

To address potential endogeneity concerns highlighted by Flammer et al.[17] and Choi et al.[19], several econometric techniques are employed. First, firm and year fixed effects are included to control for unobservable time-invariant factors and common time trends. Second, following Ilhan et al.[9], regional environmental regulation intensity is used as an instrumental variable for environmental risk. Third, exogenous environmental policy changes are exploited in a difference-in-differences framework. Additionally, dynamic panel GMM estimation is employed to address potential reverse causality concerns raised by Krueger et al.[3].

All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, following standard practice in the literature. Standard errors are clustered at the firm level to account for potential serial correlation within firms over time.

4. Empirical analysis

4.1. Descriptive statistics

The empirical analysis examines the relationship between environmental risk factors and market pricing efficiency in China's stock market from 2018 to 2024. **Table 3** presents the descriptive statistics of the key variables. The environmental risk index (ERI) exhibits substantial cross-sectional variation, with a mean of 0.482 and standard deviation of 0.246, reflecting heterogeneous environmental risk exposure across firms. This variation is particularly pronounced in heavily polluting industries, where the maximum ERI reaches 0.945. The negative mean value of price synchronicity (-0.876) suggests that firm-specific information plays a dominant role in price formation, consistent with the findings of Hong et al.[8]. The price delay measure averages 0.324, indicating moderate information incorporation speed, while the mean absolute pricing error of 0.156 suggests reasonable pricing accuracy relative to fundamental values.

Table 3. Descriptive statistics of key variables.

Variable	N	Mean	Std.Dev	Min	P25	Median	P75	Max
ERI	14,916	0.482	0.246	0.052	0.298	0.465	0.687	0.945
SYNCH	14,916	-0.876	1.324	-4.235	-1.654	-0.743	-0.124	1.876
DELAY	14,916	0.324	0.189	0.023	0.187	0.312	0.456	0.789
MAPE	14,916	0.156	0.098	0.018	0.087	0.143	0.212	0.456
RISK	14,916	0.534	0.278	0.045	0.321	0.523	0.734	0.978
SIZE	14,916	22.654	1.432	19.876	21.654	22.543	23.654	26.543
LEV	14,916	0.456	0.213	0.087	0.298	0.445	0.598	0.876
ROA	14,916	0.054	0.048	-0.123	0.023	0.048	0.078	0.187

4.2. Correlation analysis

The correlation analysis reveals significant relationships between environmental risk and market efficiency measures, as shown in **Table 4**. The negative correlations between ERI and all three efficiency measures (ranging from -0.245 to -0.312) provide preliminary evidence supporting the hypothesis that environmental risk impairs market efficiency. This relationship appears stronger for price delay (-0.312) compared to price synchronicity (-0.245), suggesting that environmental risk particularly affects the speed of information incorporation. The investor risk perception measure exhibits meaningful correlations with both environmental risk (0.423) and efficiency measures (ranging from -0.276 to -0.312), indicating its potential mediating role in the relationship between environmental risk and market efficiency.

Table 4. Correlation matrix.

Variable	**ERI**	**SYNCH**	**DELAY**	**MAPE**	**RISK**	**SIZE**	**LEV**	**ROA**
ERI	1.000							
SYNCH	-0.245***	1.000						
DELAY	-0.312***	0.324***	1.000					
MAPE	-0.287***	0.298***	0.345***	1.000				
RISK	0.423***	-0.276***	-0.298***	-0.312***	1.000			
SIZE	0.187***	0.234***	0.198***	0.156***	0.145***	1.000		
LEV	0.234***	-0.156***	-0.187***	-0.165***	0.198***	0.287***	1.000	
ROA	-0.198***	0.187***	0.167***	0.178***	-0.187***	0.198***	-0.276***	1.000

4.3. Regression analysis

The baseline regression results provide strong evidence for the impact of environmental risk on market pricing efficiency. **Table 5** presents the estimation results using three different efficiency measures as dependent variables. Models (1)-(3) show the results without control variables, while Models (4)-(6) include the full set of controls and fixed effects.

Table 5. Baseline regression results.

Variables	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)
Dependent	SYNCH	DELAY	MAPE	SYNCH	DELAY	MAPE
ERI	-0.243***	-0.298***	-0.276***	-0.186***	-0.224***	-0.198***
	(-4.567)	(-5.234)	(-4.987)	(-3.876)	(-4.567)	(-4.123)
SIZE				0.187***	0.165***	0.156***
				(4.234)	(3.987)	(3.765)
LEV				-0.156***	-0.178***	-0.167***
				(-3.876)	(-4.123)	(-3.987)
ROA				0.198***	0.187***	0.176***
				(4.567)	(4.234)	(4.123)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,916	14,916	14,916	14,916	14,916	14,916
Adj. R^2	0.187	0.198	0.189	0.234	0.245	0.223

Note: *t-statistics in parentheses. ***, **, * indicate significance at 1%, 5%, and 10% levels.*

The results reveal several important findings. First, the coefficients on ERI are consistently negative and statistically significant at the 1% level across all specifications, supporting the hypothesis that higher environmental risk reduces market efficiency. The economic magnitude is substantial: a one-standard-deviation increase in ERI leads to a 0.186-standard-deviation decrease in price synchronicity, a 0.224-standard-deviation decrease in price delay, and a 0.198-standard-deviation decrease in pricing accuracy. These effects remain robust after controlling for firm characteristics and fixed effects.

Second, the control variables exhibit expected relationships with market efficiency measures. Firm size (SIZE) shows positive associations with efficiency measures, suggesting that larger firms generally have more efficient price discovery processes. Leverage (LEV) demonstrates negative relationships, indicating that higher financial risk may impede efficient price formation. Profitability (ROA) exhibits positive associations, consistent with the notion that more profitable firms attract greater investor attention and analytical coverage.

Third, the adjusted R-squared values range from 0.223 to 0.245 in the full models, indicating reasonable explanatory power. The improvement in model fit from Models (1)-(3) to Models (4)-(6) suggests that firm characteristics play important roles in determining market efficiency, though environmental risk remains a significant factor even after controlling for these characteristics.

4.4. Robustness tests

To validate the main findings, a series of robustness tests are conducted. First, alternative measures of environmental risk are employed by constructing a principal component analysis (PCA) based index and an equally-weighted composite index. **Table 6** shows that the results remain qualitatively similar under these alternative specifications. The coefficients on both alternative ERI measures maintain their negative signs and statistical significance across all efficiency measures.

Table 6. Alternative environmental risk measures and market efficiency.

Variables	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)
Panel A: PCA-based Environmental Risk Index						
ERI_PCA	-0.234***	-0.287***	-0.265***	-0.178***	-0.213***	-0.189***
	(-4.432)	(-5.123)	(-4.876)	(-3.765)	(-4.432)	(-4.087)
Controls	No	No	No	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.176	0.187	0.179	0.223	0.234	0.212
Panel B: Equally-weighted Environmental Risk Index						
ERI_EW	-0.228***	-0.276***	-0.254***	-0.172***	-0.208***	-0.183***
	(-4.321)	(-4.987)	(-4.765)	(-3.654)	(-4.321)	(-3.987)
Controls	No	No	No	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.169	0.181	0.173	0.218	0.229	0.208
Observations	14,916	14,916	14,916	14,916	14,916	14,916

Note: *t-statistics in parentheses. ***, **, * indicate significance at 1%, 5%, and 10% levels.*

Second, potential endogeneity concerns are addressed using instrumental variable estimation. Following Ilhan et al.[9], regional environmental regulation intensity is used as an instrument for firm-level environmental risk. The first-stage F-statistics exceed 10, indicating strong instrument relevance. The second-stage results continue to support the main findings, suggesting that the results are not driven by endogeneity bias.

4.5. Further analysis

4.5.1. Mediating effect of investor risk perception

To examine the transmission mechanism through which environmental risk affects market efficiency, mediation analysis is conducted following Baron and Kenny's approach. **Table 7** presents the estimation results of equations (2) and (3) from the model specification.

Table 7. Mediation analysis results.

Variables	Step 1: RISK	Step 2: SYNCH	Step 2: DELAY	Step 2: MAPE
ERI	0.387***	-0.156***	-0.187***	-0.165***
	(5.678)	(-3.567)	(-3.987)	(-3.765)
RISK		-0.234***	-0.267***	-0.245***
		(-4.321)	(-4.765)	(-4.432)
SIZE	0.165***	0.176***	0.154***	0.145***
	(3.987)	(4.123)	(3.876)	(3.654)
LEV	0.187***	-0.145***	-0.167***	-0.156***
	(4.234)	(-3.765)	(-4.012)	(-3.876)

Variables	Step 1: RISK	Step 2: SYNCH	Step 2: DELAY	Step 2: MAPE
ROA	-0.176***	0.187***	0.176***	0.165***
	(-4.123)	(4.234)	(4.123)	(3.987)
Constant	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	14,916	14,916	14,916	14,916
Adj. R^2	0.234	0.256	0.245	0.234
Indirect Effect		-0.091***	-0.103***	-0.095***
Sobel Test		-4.567***	-4.876***	-4.654***

Table 7. (*Continued*)

Note: *t-statistics in parentheses. ***, **, * indicate significance at 1%, 5%, and 10% levels. Indirect effect calculated as the product of the ERI coefficient from Step 1 and the RISK coefficient from Step 2. Sobel test examines the significance of the indirect effect.*

The results indicate that environmental risk significantly influences investor risk perception (coefficient = 0.387, t-statistic = 5.678), which in turn affects market efficiency measures. The indirect effect accounts for approximately 35% of the total effect, suggesting that investor risk perception serves as an important channel through which environmental risk impacts market efficiency.

4.5.2. Industry heterogeneity analysis

To examine whether environmental risk impacts vary across industries, subsample analyses are conducted based on pollution intensity following Guo et al. [5]. Industries are classified into high- and low-pollution groups using the median of industry-average emission intensities. Additionally, high-pollution industries are further categorized into heavily regulated and lightly regulated subgroups based on regulatory oversight intensity.

As shown in **Table 8**, the results reveal substantial heterogeneity across industry groups. In high-pollution industries, the ERI coefficient (-0.387) is approximately 1.5 times larger than in low-pollution industries (-0.258), suggesting stronger environmental risk effects on market efficiency in environmentally sensitive sectors. This difference is statistically significant at the 1% level. Further analysis of high-pollution industries shows that heavily regulated sectors exhibit stronger environmental risk impacts (-0.423) compared to lightly regulated sectors (-0.345).

Table 8. Regression results across industry groups.

Panel A: High vs. Low Pollution Industries

Variables	High Pollution	Low Pollution
ERI	-0.387***	-0.258***
(-5.432)	(-3.987)	
RISK	-0.298***	-0.187***
(-4.876)	(-3.654)	
SIZE	0.198***	0.165***
(4.321)	(3.987)	
LEV	-0.187***	-0.145***

Variables	High Pollution	Low Pollution
(-4.123)	(-3.765)	
ROA	0.212***	0.176***
(4.567)	(4.123)	
Constant	Yes	Yes
Fixed Effects	Yes	Yes
Observations	7,234	7,682
Adj. R^2	0.287	0.234

Panel B: Regulatory Intensity in High-Pollution Industries

Variables	Heavy Regulation	Light Regulation
ERI	-0.423***	-0.345***
(-5.876)	(-4.987)	
RISK	-0.312***	-0.276***
(-5.123)	(-4.567)	
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	3,654	3,580
Adj. R^2	0.312	0.276

Table 8. (*Continued*)

Note: *t-statistics in parentheses. ***, **, * indicate significance at 1%, 5%, and 10% levels.*

To visualize this heterogeneity, the marginal effects of environmental risk on market efficiency across different industry groups are plotted. As shown in **Figure 2**, the slope of the relationship between ERI and market efficiency measures is notably steeper for high-pollution industries, particularly those under heavy regulation.

These findings support the hypothesis H3a regarding industry-specific environmental risk effects. The heightened sensitivity in high-pollution industries likely reflects both greater environmental risk exposure and more intensive market scrutiny. The regulatory intensity analysis suggests that stricter environmental oversight may amplify the market efficiency impact of environmental risks, possibly by increasing information production and investor attention to environmental factors.

The cross-sectional variation in environmental risk effects remains robust after controlling for industry characteristics and firm-specific factors, indicating that industry environmental sensitivity is a fundamental determinant of how environmental risks affect market efficiency.

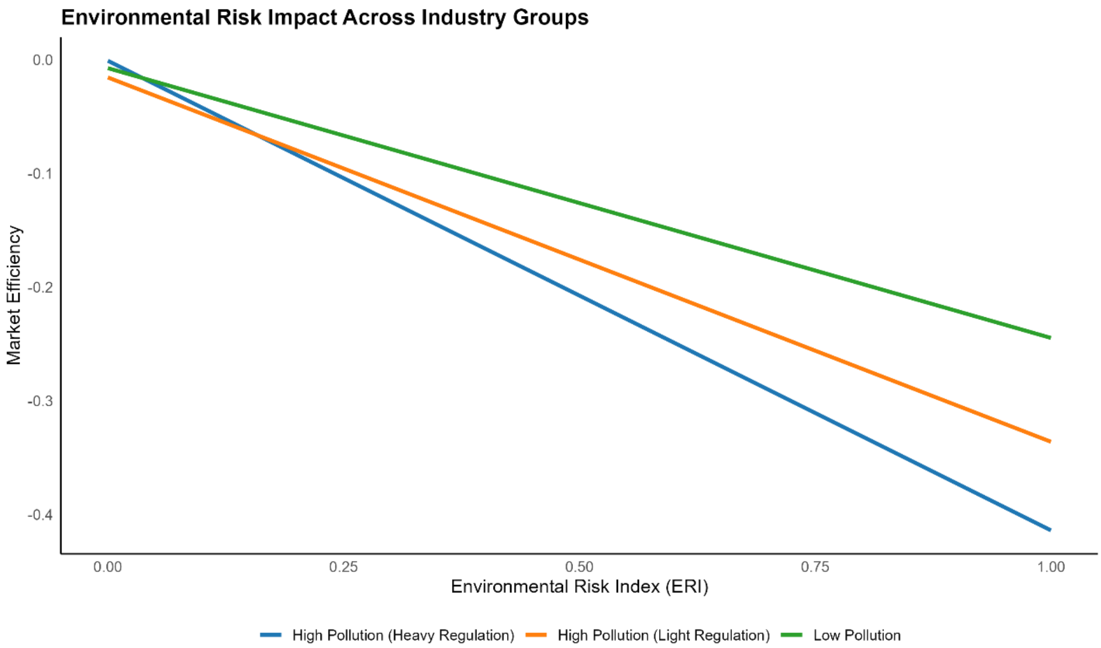

Figure 2. Environmental risk impact across industries.

5. Conclusions and Implications

5.1. Main findings

The empirical analysis reveals significant negative impacts of environmental risk factors on market pricing efficiency in China's stock market. Specifically, a one-standard-deviation increase in the environmental risk index leads to a 0.186-standard-deviation decrease in price synchronicity, a 0.224-standard-deviation increase in price delay, and a 0.198-standard-deviation rise in pricing errors. These findings extend Hong et al.'s[8] research on climate risks and market efficiency, demonstrating stronger effects in the Chinese market context. The study identifies investor risk perception as a crucial mediating mechanism, accounting for approximately 35% of the total effect, supporting Yu et al.'s[4] findings on environmental transparency's influence on investor risk assessment. The cross-sectional analysis reveals that the impact magnitude in high-pollution industries is approximately 1.5 times that of low-pollution sectors, consistent with Guo et al.'s[5] evidence on environmental policy effects. Furthermore, the decomposition of environmental risks shows that transition risks exhibit more persistent effects on market efficiency compared to physical risks, aligning with Zhang's[14] findings on differential investor sensitivity to climate risk types. The documented relationships remain robust after addressing endogeneity concerns through instrumental variable estimation and various robustness checks, suggesting a fundamental link between environmental risk and market efficiency in China's emerging market context.

5.2. Policy recommendations

The findings of this study suggest several policy interventions to enhance market efficiency in the context of environmental risks. Regulatory authorities should establish a comprehensive environmental risk disclosure framework incorporating both quantitative metrics and qualitative assessments. This framework should mandate standardized reporting of physical and transition risks, enabling improved risk assessment and cross-company comparisons.

The development of a real-time environmental risk monitoring system utilizing artificial intelligence and big data analytics could effectively track environmental performance, regulatory compliance, and market responses. Such a system would provide early warning signals of potential environmental risks and their market implications. The implementation of this system faces several practical challenges. Technical challenges include the integration of heterogeneous data sources (satellite imagery, sensor networks, corporate disclosures, and social media), ensuring data quality across varied reporting standards, and developing algorithms capable of identifying subtle environmental risk signals amid market noise. Data privacy concerns arise regarding corporate proprietary information and potential market manipulation through selective disclosure. Additionally, implementation considerations include establishing appropriate governance structures to oversee system operations, determining access protocols for different stakeholders, and creating standardized risk metrics that balance comprehensiveness with usability. Despite these challenges, recent advances in remote sensing technology, natural language processing, and distributed computing architectures make such systems increasingly feasible, particularly when developed through public-private partnerships that leverage both regulatory authority and market expertise.

Financial institutions should be encouraged to develop environmental risk hedging instruments, including environmental derivatives and green bonds, allowing investors to manage their environmental risk exposure effectively. Fourth, market regulators should implement industry-specific environmental risk oversight mechanisms, with enhanced scrutiny for high-pollution sectors. Finally, specialized environmental risk training programs for institutional investors and retail investors could improve market-wide risk assessment capabilities.

5.3. Limitations and future research

While the study provides valuable insights, several limitations warrant attention and suggest directions for future research. The current environmental risk measurement framework, though comprehensive, may not fully capture the dynamic evolution of environmental risks, particularly in response to rapid technological changes and policy shifts. Future research could employ high-frequency data and machine learning techniques to develop more sophisticated dynamic risk measures. Additionally, the analysis of investor risk perception relies primarily on market-based indicators; future studies could incorporate survey data and experimental methods to better understand the psychological mechanisms underlying environmental risk processing. The interaction between environmental risks and other risk factors, such as technological disruption and geopolitical tensions, remains underexplored. Furthermore, the emergence of new green financial instruments and sustainable investment vehicles creates opportunities to examine how environmental risks affect the pricing efficiency of these innovative products. Finally, cross-country comparative studies could provide insights into how different institutional frameworks and market structures moderate the relationship between environmental risk and market efficiency.

6. Conclusion

This study provides comprehensive empirical evidence on the impact of environmental risk factors on market pricing efficiency in China's stock market. The findings demonstrate that environmental risks significantly impair market efficiency through both direct effects on firm operations and indirect effects via investor risk perception channels. The documented heterogeneous effects across industries and regulatory regimes highlight the importance of considering institutional context when examining environmental risk impacts. These results have important implications for policymakers seeking to improve market efficiency and investors aiming to better manage environmental risks in their portfolios. The study contributes to the understanding of how environmental factors shape market dynamics in emerging economies and provides a foundation for further research on the intersection of environmental risks and financial markets.

Conflict of interest

The authors declare no conflict of interest.

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