Corporate Climate Risk Disclosure and Stock Return Anomalies: Evidence from Textual Analysis of Chinese A-Shares

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Abstract

Climate risk management is becoming an integral aspect for firms to meet the evolving demands of markets and government policies. A growing number of firms incorporate climate-related disclosures into their annual reports. This non-financial information may not be fully exploited by investors, holds the potential to serve as a climate-related factor in asset pricing. This essay quantifies firm-level climate risk disclosures by analysing corporate annual reports of Chinese A-share listed companies through Python-based text mining. Following Lin and Wu (2023), we utilize natural language processing to extract and measure the frequency of key climate-related terms, constructing a comprehensive dataset of climate risk disclosure (CRD) scores. Our results indicate that firms with lower climate disclosures tend to deliver higher returns, reflecting that a potential risk premium demanded by investors for holding stocks with lower transparency. Furthermore, we construct a climate risk exposure factor, denoted as RCRD, by going long on the top CRD decile and short on the bottom CRD decile, based on CRD scores. We find that RCRD earns significant abnormal return. Especially, the loadings on RCRD factor are positively and significantly associated with future portfolio returns in Fama Macbeth regressions, suggesting that climate risk exposure contains the return predictive power. We argue that climate risk exposure represents a novel stock anomaly, offering a valuable complement to existing traditional asset pricing models.

1. Introduction

Firm characteristics-based anomalies are typically defined as systematic deviations from expected asset pricing models, arising from market participants' mispricing of firms' fundamental attributes. With the increasing significance of climate governance, evaluating non-traditional risks has become essential in investment decision-making processes. Chinese government aims to achieve carbon peak and carbon neutrality by 2030 and 2060, respectively. As of 2023, China has emerged as the largest producer of wind and solar power in the world. An increasing number of firms choose to manage climate risk by disclosing climate-related information in their annual reports. This practice enables firms to meet market expectations for transparency regarding climate risk exposure. This essay examines whether climate risk exposure can serve as a valid factor in achieving abnormal returns, thereby qualifying as a new stock anomaly to complement existing traditional asset pricing models.

The efficient-market hypothesis (EMH) asserts that financial markets are "informationally efficient," meaning that asset prices should fully reflect all available information in the market (Fama, 1970). However, extensive empirical evidence challenges the EMH, particularly in emerging markets where inefficiencies such as information asymmetry, behavioural biases, and market constraints prevail. These inefficiencies disrupt market efficiency, often manifesting as anomalies (Grossman & Stiglitz, 1980; Barberis et al., 1998). In less mature markets, limited investor sophistication and weak regulatory environments exacerbate pricing distortions, creating opportunities to explore non-traditional determinants of stock returns, including corporate climate risk disclosures, which are often ignored by market participants. Such inefficiencies associated with climate risk may result in stock return anomalies, providing a unique framework to assess the impact of climate-related transparency on asset pricing (Hong et al., 2019; Bolton & Kacperczyk, 2021).

Climate risk, broadly categorized into physical risks and transition risks, poses significant challenges to firm performance and valuation (Bansal et al., 2017). Physical risks, such as extreme weather events, directly impact firms' operations and supply chains, while transition risks, stemming from regulatory changes and evolving consumer preferences, affect strategic planning. These risks are not only material but systemic, influencing entire industries and financial markets. Firms' disclosures of climate risks play a pivotal role in mitigating information asymmetry between firms and investors. Transparent disclosures enable investors to better evaluate long-term viability and risk exposure, particularly in uncertain environments (Chatterji et al., 2009). However, climate risk disclosures are often embedded within broad Environmental, Social, and Governance (ESG) frameworks, which may dilute the focus on climate-specific factors (Chatterji et al., 2009). This dilution hampers precise assessments of the impact of climate disclosures on portfolio and stock returns, highlighting the need for studies that specifically isolate these effects (Ilhan et al., 2021). This study fills this gap by introducing a firm-level Climate Risk Disclosure (CRD) measure whether this stock anomaly exist in China's A-share market.

The Chinese A-share market provides an ideal setting for investigating climate risk disclosures. The market is characterized by a dominance of retail investors, who account for over 80% of trading volumes (Yu et al., 2019). Retail investors' speculative behaviours and limited access to comprehensive information amplify market inefficiencies. This lack of transparency often leads investors to perceive low-disclosure firms as riskier due to incomplete or unclear information. As a result, they demand a higher risk premium to compensate for potential uncertainties, which is directly reflected in higher expected returns for these stocks. In 2021, the Chinese government launched a national emissions trading scheme to encourage firms to enhance their disclosure practices, aligning with its interim goal of reaching peak carbon emissions by 2030 and its long-term objective of achieving carbon neutrality by 2060.

Although ESG development in China began later than in Europe and the United States, its progress has been rapid, with the number of social responsibility reports increasing significantly from 32 in 2006 to over 2,000 by 2019 (Albuquerque et al., 2019). Unlike Europe, where mandatory ESG disclosure policies are prevalent, China relies on a voluntary approach, emphasizing firms' proactive engagement in sustainability initiatives. By contrast, the United States emphasizes market-driven mechanisms and shareholder activism to influence corporate disclosure practices. These differences in regulatory frameworks highlight the varying roles of policy and market forces in shaping climate transparency across regions. China's policy-driven approach provides a unique context to explore how climate disclosures influence asset pricing and stock return anomalies.

This study leverages textual analysis to construct a robust CRD measure, analysing corporate annual reports of Chinese A-share firms from 2002 to 2022. Unlike traditional financial data analysis, textual analysis captures nuanced contextual and linguistic patterns in corporate disclosures, enabling the identification of implicit signals about firms' climate strategies and risks (Luo et al., 2015; Ilhan et al., 2021). The CRD measure is based on a lexicon of 155 climate-related keywords derived from authoritative sources, including Chinese government work reports and international policy documents. CRD is calculated as the ratio of climate-related terms to the total word count in annual reports, offering a standardized and scalable metric for assessing firms' climate risk communication. By quantifying CRD, this study aims to uncover its predictive power for identifying stock return anomalies. The essay contributes to the broader discourse on climate finance, highlighting how firm-level transparency influences market efficiency and investment decisions.

This study develops a Climate Risk Disclosure (CRD) measure to explore its relationship with stock returns, providing both descriptive insights and predictive analyses. We first examine the distribution of CRD across industries and firm characteristics, identifying sector-specific patterns in climate disclosures and variations in attributes such as firm size, age, and profitability. These patterns highlight the heterogeneity in corporate climate communication practices. Subsequently, we investigate the impact of CRD on stock returns through both stock-level and portfolio-level analyses. The results reveal that stocks with lower levels of CRD consistently exhibit higher returns, suggesting that investors demand a risk premium for holding stocks with limited climate risk transparency. Moreover, we construct a climate risk exposure portfolio (RCRD), demonstrating its potential as a standalone factor with significant high risk-adjusted returns. Fama Macbeth regressions shows the RCRD factor contains the significantly positive premium and furtherly confirms the RCRD has the return predictive power for future portfolio returns.

Our study contributes to the literature as follows. First, we introduce a firm-level measure of Climate Risk Disclosure (CRD) using textual analysis techniques, capturing the extent of firms' willingness to voluntarily disclose and manage climate risks in the Chinese A-share market. This willingness reflects not only a firm's strategic alignment with regulatory and societal expectations but also its commitment to addressing environmental uncertainties, which may influence investor confidence and market perceptions. By employing a structured approach to keyword selection and processing, the CRD measure provides a systematic and replicable metric for assessing climate-related corporate communication. Second, we find climate risk exposure could serve as a novel stock anomaly. We provide empirical evidence on the relationship between climate disclosures and stock/portfolio return, isolating the climate risk factor from broader ESG frameworks to clarify its distinct role in asset pricing at both stock and portfolio levels. Third, our study advances the understanding of financial markets in developing countries by offering evidence on the role of climate risk disclosure in the Chinese stock market. This study highlights sectoral and firm-level variations in climate communication, shedding light on how climate transparency interacts with stock market dynamics in an emerging market context.

Beyond theoretical insights, this study offers practical implications for investors, policymakers, and corporate managers. For investors, incorporating CRD into investment strategies can identify mispriced assets, enhancing portfolio performance while addressing sustainability goals (Bolton & Kacperczyk, 2021). For policymakers, the findings underscore the need for standardized and transparent climate disclosure frameworks to reduce asymmetries and improve market efficiency. Initiatives such as the Task Force on Climate-related Financial Disclosures (TCFD) provide a useful foundation but require further adaptation for emerging markets like China (Xie et al., 2021). For corporate managers, the results demonstrate the tangible benefits of improving climate transparency, including attracting long-term investors and aligning with regulatory expectations.

This essay is organized as follows. Section 2 reviews the literature on market efficiency, asset pricing anomalies, and climate risk disclosure, providing a theoretical foundation for the study. Section 3 describes the methodology and data used to construct the CRD measure and examine its relationship with stock returns. Section 4 presents the empirical results, including descriptive analyses, portfolio-level findings, and regression-based tests. Section 5 concludes the essay with a discussion of the implications and potential avenues for future research.

2. Literature Review

2.1. Efficient Market Hypothesis and Asset Pricing Foundations

The Efficient Market Hypothesis (EMH) propose that financial markets are "informationally efficient" and that asset prices should fully reflect all available information (Fama, 1970). According to EMH, investors cannot consistently achieve higher returns than average market returns on a risk-adjusted basis since asset prices are already incorporated and immediately respond to public and private information. In an efficient market, intense competition among investors will make arbitrage opportunities quickly eliminated, thus making it difficult to outperform the market over time. The Efficient Market Hypothesis (EMH) classifies market efficiency into three forms: weak, semi-strong, and strong, reflecting the extent to which past, public, and all information, respectively, are incorporated into prices (Fama, 1970). The evidence supporting semi-strong form efficiency is particularly significant, as it implies that fundamental and technical analysis should not yield persistent excess returns (Fama, 1991).

Building on the concept of market efficiency, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) provides a single-factor model that explains stock returns based on their sensitivity to market-wide movements. CAPM posits that the expected return on a security is determined by its beta, a measure of systematic risk, meaning investors are only compensated for market-wide risk and not firm-specific risks. Later, Fama and French (1993) expanded this approach by introducing a multifactor model, incorporating size (SMB) and book-to-market (HML) factors in addition to the market factor. Jegadeesh and Titman (1993) found that stocks that have recently performed well often continue to do so in the short term, while poor performers tend to underperform. Carhart (1997) added a momentum factor, showing that stocks that performed well in the past continue to do so in the short term, indicating that price momentum plays a significant role in asset pricing. Fama and French (2015) expanded the model by adding two factors, profitability (RMW) and investment (CMA), to capture variations in operating profitability and investment behaviour, respectively. The addition of these new factors helps to explain cross-sectional changes in stock returns that are not explained by the CAPM.

The validity of the EMH and its associated asset pricing models has faced significant scrutiny due to the persistent presence of market anomalies. Grossman and Stiglitz (1980) contended that perfectly efficient markets would disincentivize investors from acquiring costly information, resulting in inherent inefficiencies driven by information asymmetries. Such anomalies, including size and value effects, highlight limitations in traditional models and suggest that financial markets may not fully reflect all available information. This opens the door to exploring additional non-traditional factors, such as climate-related disclosures, which could play a pivotal role in shaping asset pricing dynamics in an increasingly complex financial environment.

2.2. Market Inefficiencies and Stock Return Anomalies

Some research has introduced behavioural finance to explain these inefficiencies, pointing to investor biases as a source of deviation from fundamental values. For example, Barberis, Shleifer, and Vishny (1998) proposed the idea of style investing, where investors exhibit preferences for certain styles (e.g., growth or value), resulting in price co-movement among assets within the same style category. This behaviour-driven demand can cause style stocks to deviate from intrinsic values. Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) highlighted how overconfidence leads investors to overreact to new information, creating price deviations. Overconfident investors may contribute to excessive volatility and short-term mispricing, which will later be corrected as additional information appears. Such behaviourally driven mispricing strengthens the argument for expanding asset pricing to incorporate non-traditional factors, which may hold valuable insights for understanding return predictability.

In addition to traditional financial metrics, research has increasingly explored non-financial factors that may influence stock returns. These non-financial risk factors encompass various aspects beyond Environmental, Social, and Governance (ESG) considerations, such as corporate reputation, customer satisfaction, innovation capacity, and intellectual capital. Studies have shown that these intangibles can play a substantial role in asset pricing and may offer predictive insights into firm performance, particularly in industries where such factors significantly impact competitiveness and value creation. For instance, Fombrun and Shanley (1990) suggest that firms with strong reputations enjoy favourable investor perceptions, potentially enhancing their valuation. Mizik and Jacobson (2003) found that innovation capacity, as a reflection of a firm's adaptability, positively affects stock returns, while Edmans (2011) demonstrated that companies with high employee satisfaction tend to outperform in the stock market.

These insights suggest that non-financial factors, like intangible assets and firm characteristics, challenge traditional asset pricing models that focus only on financial data. This gradual expansion of the asset pricing framework supports a broader understanding of what constitutes firm risk and value, providing a logical transition to exploring climate risk as an emerging dimension in asset pricing.

2.3. Climate Risk in Assets Pricing

As asset pricing models evolve, increasing attention has been paid to non-financial factors, including Environmental, Social, and Governance (ESG) considerations and the broader concept of climate risk. ESG metrics aim to evaluate sustainability and ethical practices within firms, encompassing environmental initiatives, social responsibility, and governance structures. These factors provide a more comprehensive view of a firm's operations and risk profile beyond traditional financial analysis, influencing investor behaviour and market performance. Derwall et al. (2005) documented the "eco-efficiency premium," demonstrating that environmentally proactive firms achieve superior stock performance. Similarly, Kempf and Osthoff (2007) highlighted that socially responsible investments yield positive excess returns, underscoring the relevance of ESG in asset pricing.

Despite its growing adoption, the ESG framework is not without limitations. Inconsistencies in scoring methodologies and a lack of transparency often undermine their reliability in financial modelling (Chatterji et al., 2009). Additionally, ESG ratings rely on voluntary, non-standardized corporate disclosures, leading to inconsistencies, selective reporting, and potential "greenwashing" (Delmas & Burbano, 2011). Variability among rating providers further complicates comparisons, as divergent methodologies and criteria result in conflicting scores for the same company (Berg et al., 2020). This has prompted a focus on more specific elements within ESG, particularly climate risk, due to its direct and quantifiable impact on firm valuation and performance. Climate risk, broadly categorized into physical and transition risks, has emerged as a distinct and critical factor in asset pricing. Physical risks encompass direct impacts such as extreme weather events and sea-level rise, while transition risks arise from regulatory changes, shifts in market preferences, and the transition to a low-carbon economy (Bolton & Kacperczyk, 2021).

Empirical research highlights the financial relevance of climate risk. Hong, Li, and Xu (2019) found that firms exposed to high physical risks often suffer lower valuations due to reduced future cash flows. Similarly, Ilhan, Krueger, and Sautner (2021) demonstrated that transition risks, such as policy-induced compliance costs, materially affect stock prices, particularly in carbon-intensive sectors. Bansal, Ochoa, and Kiku (2017) further showed that firms with high emissions exposure face higher risk premiums, reinforcing the importance of integrating climate risk into asset pricing models. These studies suggest that climate risk has systemic implications, influencing cross-sectional stock returns in ways traditional financial metrics fail to capture.

Incorporating climate risk into asset pricing not only enhances model accuracy but also improves market efficiency by reducing information asymmetry. Transparent climate risk disclosures allow investors to make more informed decisions, aligning asset prices more closely with environmental exposure. For instance, Bolton and Kacperczyk (2021) found that firms providing comprehensive climate disclosures are better priced by markets, particularly in climate-sensitive industries. This targeted approach to climate risk facilitates precise risk assessment and portfolio construction, aligning with investor preferences for sustainable investment strategies, such as green bonds and low-carbon indices (Andersson et al., 2016). In summary, the integration of climate risk into asset pricing frameworks represents a significant step forward in understanding firm risk and value in a changing environmental landscape.

2.4. Climate Risk Disclosure

Research on climate risk addressing its implications for financial markets, corporate strategies, and macroeconomic stability. Climate risk typically includes physical risks, like extreme weather, and transition risks, such as regulatory shifts and technological changes. Bolton and Kacperczyk (2021) highlight how carbon emissions are priced into firm equity valuations, demonstrating that firms with higher emissions face higher costs of capital due to heightened exposure to transition risks. Similarly, Giglio et al. (2021) illustrate that climate risk significantly impacts sovereign bond yields, showing how countries with greater climate vulnerability face higher borrowing costs.

In addition to firm-level and country-level analyses, climate risk has been explored in the context of financial market stability. Battiston et al. (2017) argue that climate-related risks can propagate through financial networks, amplifying systemic risk due to interconnected exposures among financial institutions. Similarly, Dietz et al. (2016) assess the macroeconomic implications of climate risks, showing that unchecked climate change could result in significant economic output losses and financial instability. These studies provide a broader perspective, demonstrating how climate risk affects not only individual firms or sectors but also financial systems and global economic growth. As a result, understanding climate risk has become critical for policymakers, financial regulators, and investors seeking to mitigate its adverse impacts.

Given the systemic risks posed by climate change, transparent and standardized climate risk disclosures are increasingly seen as a means to mitigate information asymmetry and enhance market efficiency. Quantifying climate risk disclosure has become a critical area of research, employing advanced methodologies to measure corporate transparency on climate-related issues. Textual analysis techniques, such as keyword frequency counts and natural language processing (NLP), are widely used to extract relevant information from corporate reports. For instance, Luo et al. (2015) developed a disclosure index based on climate-related keywords in sustainability reports to assess corporate climate communication quality. Similarly, Ilhan, Sautner, and Vilkov (2021) utilized machine learning to analyse climate-related discussions in earnings call transcripts, uncovering links between disclosure patterns and stock price reactions. These studies emphasize the importance of standardized and transparent data sources, such as disclosures aligned with the Task Force on Climate-related Financial Disclosures (TCFD) recommendations, which aim to harmonize reporting practices and improve comparability across firms. As data-driven methods evolve, climate risk disclosure quantification provides deeper insights into the relationship between transparency, investor behaviour, and firm valuation.

Lin and Wu (2023) demonstrate that climate risk disclosure plays a critical role in reducing stock price crash risk by improving transparency and reducing information asymmetry. Their findings highlight the importance of incorporating climate information into financial decision-making and the need for standardized climate risk disclosures to enhance market stability and investor trust. They also developed a firm-level Climate Risk Disclosure (CRD) measure using a textual analysis methodology that draws from Chinese government work reports and other climate-related textual sources. Lin and Wu (2023) argue that this methodology effectively quantifies the degree of a firm's climate risk disclosure, providing a valuable metric for assessing the financial implications of climate communication. We adopt Lin and Wu's (2023) textual analysis methodology, using a dataset of corporate annual reports from Chinese A-share listed firms spanning 2002 to 2022. The CRD measure is calculated as the ratio of climate-related keywords to the total word count in each report. Specifically, we use a lexicon of 155 keywords, expanded from an initial set of 110 terms identified in Chinese government work reports and international climate policy documents, ensuring comprehensive coverage of climate-related terminology.

2.5. Behavioral Finance and Climate Risk Pricing

Behavioral finance provides a compelling lens through which to examine how climate risk disclosure (CRD) influences investor behaviour and subsequently impacts asset pricing. Unlike traditional finance theories, which assume rationality, behavioral finance recognizes that investors are influenced by cognitive biases, emotions, and heuristics, particularly when processing complex or unfamiliar information like climate risks. Overconfidence and herding behaviour, in particular, play pivotal roles in how investors interpret and react to CRD, contributing to potential mispricing of assets. Overconfidence, as described by Daniel, Hirshleifer, and Subrahmanyam (1998), leads investors to overestimate their ability to assess and predict climate risks, often resulting in excessive trading based on their subjective interpretations of disclosed information. For instance, investors may overweight firms with high CRD scores, assuming that such transparency correlates with superior environmental management, regardless of fundamental financial performance. This overreaction can lead to price deviations and increased volatility, as evidenced by Lin and Wu’s (2023) findings that higher CRD levels correlate with short-term price fluctuations, particularly in less efficient markets like China’s A-share market.

Herding behaviour further amplifies these dynamics, as investors collectively chase perceived climate-resilient firms, driving prices beyond intrinsic values. Baker, Ruback, and Wurgler (2007) suggest that institutional investors, guided by ESG mandates, often exhibit herding tendencies when allocating portfolios, disproportionately favouring firms with transparent climate disclosures. In markets dominated by retail investors, such as China, the effect is magnified by recency bias, where individuals react strongly to recent climate-related announcements without considering their long-term implications (Tian et al., 2018). This behaviour is particularly pronounced during periods of heightened regulatory scrutiny or environmental crises, where speculative trading fuelled by incomplete or ambiguous disclosures contributes to price anomalies. Herding and overconfidence, although distinct, are often intertwined in less efficient markets, as limited information availability and inconsistent disclosure amplify investors’ reliance on subjective judgment or collective trends.

Information asymmetry further exacerbates these effects. In markets where disclosure standards are inconsistent, as noted by Lin and Wu (2023), CRD becomes a critical determinant of investor perception. Firms that voluntarily disclose detailed climate risk information may experience a temporary valuation premium as investors interpret such transparency as a signal of superior management quality or reduced environmental risk. However, selective or inconsistent disclosures can lead to "greenwashing," undermining investor trust and contributing to long-term mispricing (Delmas & Burbano, 2011). Bolton and Kacperczyk (2021) found that firms with transparent climate disclosures tend to attract more institutional investors, further emphasizing the role of information asymmetry in shaping market dynamics. Additionally, Berg, Koelbel, and Rigobon (2020) highlighted how inconsistencies in ESG rating methodologies contribute to fragmented investor interpretations, amplifying the market impact of voluntary disclosures. This aligns with Hong, Li, and Xu's (2019) findings that climate-sensitive firms in less transparent markets face higher pricing volatility due to heightened speculative behaviour, especially during periods of regulatory shifts or environmental crises.

CRD's role as a firm-level characteristic offers a unique opportunity to identify stock return anomalies by bridging the gap between behavioral finance and information asymmetry theories. In markets where climate information is incomplete or inconsistently disclosed, CRD provides a standardized framework to quantify how firms communicate climate risks, enabling an analysis of investor sentiment and behavioral biases. For instance, firms with low CRD scores may be systematically undervalued due to perceptions of heightened environmental risks or poor management practices. This underpricing aligns with Hong, Li, and Xu's (2019) findings that market inefficiencies linked to environmental risks often result in pricing deviations that are later corrected as investors reassess firm fundamentals. Similarly, Lin and Wu (2023) argue that CRD acts as a lens to reveal market inefficiencies and investor behaviour in the context of environmental risks, particularly in markets characterized by high retail participation and sentiment-driven trading. Furthermore, Bolton and Kacperczyk (2021) highlight how climate transparency can influence capital allocation by signalling reduced risk, thereby altering investor preferences and market pricing dynamics. These insights underscore CRD's potential to capture both behavioral and informational dimensions of stock return anomalies, particularly in emerging markets where information asymmetry is more pronounced.

2.6. Characteristics of the Chinese Stock Market and Climate Policy

China's A-share market is characterized by unique features that distinguish it from developed markets, notably the dominance of retail investors and significant information asymmetry. Retail investors account for the majority of trading volumes, often exhibiting high sensitivity to public announcements and speculative behaviour (Tian et al., 2018). This investor composition exacerbates market volatility and heightens the role of corporate disclosures in shaping investor sentiment. Additionally, the limited presence of institutional investors reduces the market's capacity to efficiently process and reflect fundamental information in asset prices (Yu et al., 2019). These dynamics create an environment where standardized and reliable information, such as climate risk disclosure (CRD), can have outsized importance in mitigating mispricing and enhancing market efficiency.

In recent years, China has made significant strides in environmental and climate policies, aligning its domestic initiatives with global frameworks. However, this commitment has deep roots. Early legislation, such as the Cleaner Production Promotion Law (2002) and the Renewable Energy Law (2005), established a legal foundation for sustainable development. The 2007 National Climate Change Program outlined strategies for reducing greenhouse gas emissions and adapting to climate change, and in 2009, the government pledged to cut carbon intensity by 40%-45% by 2020 compared to 2005 levels. On the international stage, China joined the Paris Agreement in 2016, demonstrating its alignment with global climate governance. Building on this foundation, the 2020 announcement of China's carbon neutrality target by 2060 marked a pivotal moment, leading to stringent environmental regulations and incentives for corporate environmental responsibility. The introduction of China's national emissions trading scheme (ETS) in 2021 further underscored the government's commitment to integrating climate considerations into economic policies (Xie et al., 2021). These policy developments have prompted firms to enhance their climate risk disclosures, as investors and regulators increasingly demand transparency regarding environmental risks and opportunities.

Given these unique market and regulatory conditions, climate risk disclosure holds particular significance in China. In a market dominated by speculative trading and short-termism, CRD provides a standardized metric that captures firms' climate risk management and communication. By addressing information asymmetry and reducing speculative distortions, CRD enhances the market's ability to evaluate firm-level resilience to climate risks. This aligns with prior research highlighting the importance of tailored climate disclosures in improving market efficiency, particularly in emerging economies (Luo et al., 2015). Moreover, incorporating CRD into asset pricing models offers an approach to identifying stock return anomalies in the Chinese context. The dynamic interplay between regulatory developments, investor sentiment, and corporate disclosures creates opportunities for CRD to serve as a meaningful firm-level characteristic.

2.7. Empirical Approaches to Measuring Climate Risk Disclosure

Measuring Climate Risk Disclosure (CRD) has become a critical task for understanding how firms communicate their exposure to climate-related risks and opportunities. One prominent method for quantifying CRD involves textual analysis of corporate documents, such as annual reports and sustainability disclosures. Early studies, including Michelon et al. (2015), used keyword frequency analysis to quantify the extent of climate-related information in corporate communications. By identifying terms such as "carbon," "emissions," and "renewable," and standardizing their occurrence relative to document length, these studies provided approximate measures of climate communication. However, such approaches often lack contextual nuance, which is critical for understanding the depth and intent of disclosures.

More advanced approaches employ Natural Language Processing (NLP) techniques to capture thematic and tonal content in climate disclosures. For instance, Jiang (2019) used Latent Dirichlet Allocation (LDA) to categorize climate-related topics within corporate reports, offering a nuanced understanding of how firms address specific climate risks. Machine learning models, such as those based on BERT or GPT, further enhance precision by identifying specific disclosure elements, including regulatory compliance and adaptation strategies (Huang & Li, 2020). However, these sophisticated methods require substantial computational resources and large, annotated datasets, posing challenges for scalability.

In the context of the Chinese market, Lin and Wu (2023) developed a CRD measure tailored to the unique regulatory and market environment. Their methodology involved a textual analysis of corporate annual reports, drawing on climate-related keywords selected from Chinese government work reports. This approach leverages official policy documents, which serve as authoritative sources for climate-related terminology, ensuring that the lexicon reflects the priorities and language of China's regulatory framework. Government work reports provide a consistent and policy-aligned basis for understanding how firms align their disclosures with national climate goals. This alignment is particularly relevant given China’s strong policy-driven market dynamics.

Building on Lin and Wu’s (2023) framework, this study adopts a textual analysis methodology tailored to the Chinese A-share market. The dataset spans from 2002 to 2022, reflecting the period when climate-related policies and corporate disclosures began to gain prominence following China's accession to the WTO and its increasing integration into global environmental initiatives. The CRD measure is derived from a lexicon of 155 keywords, expanded from an initial set of 110 terms identified in Chinese government work reports. This approach ensures comprehensive coverage of terms relevant to climate risks and opportunities within the Chinese regulatory and market context. The CRD is calculated as the ratio of climate-related keywords to the total word count in annual reports, providing a standardized and scalable measure of firms' climate communication intensity.

3. Methodology and Data Description

3.1. CRD Measurement

The Climate Risk Disclosure (CRD) measure was constructed through textual analysis method. We first download the annual government work reports from the official website[1] of the Chinese government. The period of the reports is from 2002 to 2022. We follow the method of Luo et al. (2015) and analyse the frequency of words related to the environment, energy, and climate in these reports, recording the frequency of each keyword across different years. Through this analysis, we identify a set of the top 110 most frequently appearing keywords as a seed word collection. We then manually add common synonyms for some of these keywords to minimize matching omissions, resulting in a final set of 155 keywords. This step helps us understand the Chinese government's attention on climate risk-related issues.

After obtaining this climate risk seed word library, we use Python's network request and JSON parsing functions to download the basic information of Chinese A-share stocks listed on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) from CNINFO. This includes key fields such as company code and name, which are processed using pandas for further analysis. By matching company codes and years, we retrieve the PDF links for each company's annual report. Before the batch download of these reports, we clean the data, removing irrelevant summaries, cancelled announcements, and English titles to ensure data accuracy and consistency. This produces a file containing company codes, years, and PDF links. Guided by this file, we use Python to automate the batch download of annual report PDFs and convert them into txt format to enable direct text analysis.

The frequency of keywords appearing in the annual reports is obtained using Python's text processing (jieba) function, and weighted calculations are applied based on the character

[1] The official website of the Chinese government is www.gov.cn.

count of each keyword to determine the total keyword frequency for each company's report. Specifically, the Climate Risk Disclosure (CRD) is defined as follows:

$$\mathrm{CRD} = \frac{\mathrm{n}}{\mathrm{N}} \tag{1}$$

where n represents the total count of climate-related keywords appearing in a company's annual report in a given year, and N is the total word count of the report.

3.2. Fixed-Effects Panel Regression

In addition to CRD, we incorporate a range of firm-specific characteristics to control for other potential effects on stock returns. These characteristics include firm size (ME), measured by market capitalization to account for size effects; book-to-market ratio (BM), representing the value effect as the ratio of book value to market value; and past returns (MOM), calculated as the cumulative returns over the prior 12 months to capture momentum. We also include firm age (AGE), representing the number of years since listing, to control for maturity effects; earnings indicator (E+), defined as the percentage of firms with positive earnings, to proxy for financial performance; and dividend indicator (D+), reflecting the percentage of firms paying dividends as a measure of profitability. The effects of these variables are shown in Table 6.

To investigate the impact of Climate Risk Disclosure (CRD) on stock returns, we employ a fixed-effects panel regression approach. This method helps control for unobservable firm-specific characteristics and time-invariant that may influence returns, allowing for a more accurate estimation of the relationship between CRD and stock performance. Our regression model examines the predictive relevance of CRD by controlling for a wide range of firm-specific factors known to affect returns. The baseline model can be represented as follows:

$$
\begin{aligned}
\mathrm{RET}_{\mathrm{it}} = \alpha + \ & \beta_1 \mathrm{CRD}_{\mathrm{it}} + \beta_2 \mathrm{LOGME}_{\mathrm{it}} + \beta_3 + \beta_4 \mathrm{RET}_{\mathrm{i}\ \mathrm{t-1}} + \beta_5 \mathrm{RET}_{\mathrm{i}\ \mathrm{t-2,t-12}} + \beta_6 \mathrm{ISSUE}_{\mathrm{it}} \\
& + \beta_7 \mathrm{IVOL}_{\mathrm{it}} + \beta_8 \mathrm{ACC}_{\mathrm{it}} + \beta_9 \mathrm{AG}_{\mathrm{it}} + \beta_{10} \mathrm{IVA}_{\mathrm{it}} + \beta_{11} \mathrm{DE}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \qquad (2)
\end{aligned}
$$

where $\mathrm{RET}_{\mathrm{it}}$ is the monthly stock return for firm i at time t; CRD is the Climate Risk Disclosure score, representing the proportion of climate-related keywords in a firm's annual report; LOGME is the logarithm of firm market capitalization (ME); LOGBM is the logarithm of the book-to-market ratio (BM); $\mathrm{RET}_{\mathrm{i}\ \mathrm{t-1}}$ is the lagged return of the firm from the previous month; $\mathrm{RET}_{\mathrm{i}\ \mathrm{t-2,t-12}}$ is the cumulative return over the past 12 to 2 months; ISSUE represents share issuance, measured as the logarithmic change in shares outstanding over a 12-month period, IVOL captures idiosyncratic volatility, calculated as the standard deviation of residuals from regressing daily stock returns on market returns; ACC represents accruals, following Sloan (1996); AG denotes asset growth, following Cooper et al. (2008); IVA is the investment-to-asset ratio, as described by Lyandres et al. (2008); DE represents leverage, calculated as the ratio of total liabilities to the market value of equity.

To account for heteroskedasticity and autocorrelation in the error terms, we cluster standard errors by firms. The inclusion of control variables across models tests the robustness of the effect of CRD on stock returns while controlling for firm-specific, time-invariant characteristics.

3.3. Portfolio Construction

We obtain the monthly data for the market factor (MKT), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), investment factor (CMA), and monthly momentum factor (MOM) directly from the CSMAR database. To examine the effect of climate risk disclosure in the China A-share market, we construct portfolios based on Climate Risk Disclosure (CRD) levels.

To construct the climate risk disclosure factor (RCRD), we sort all stocks into deciles based on their CRD scores at the end of each June. The bottom CRD decile (M1) represents firms with minimal climate-related disclosures, while the top CRD decile (M10) includes firms with extensive disclosures. We form a zero-investment hedging portfolio by going long on the bottom 10% of stocks with low CRD scores (representing low-disclosure firms) and shorting the top 10% of stocks with high CRD scores (representing high-disclosure firms). The portfolio is rebalanced annually at the end of fiscal year to ensure alignment with the most recent climate disclosure data. The returns are calculated as value-weighted mean on monthly basis.

3.4. Fama-Macbeth Regression Analysis

To investigate the return predictive power of climate risk disclosure (CRD) on stock returns, we employ the Fama-MacBeth regression methodology, a widely used approach to examine whether specific factors can capture common risks across firms. We adapt this methodology to assess the impact of RCRD as a risk factor on future returns.

The Fama-MacBeth regression involves two main stages: a time-series regression and a cross-sectional regression. In the first stage, we perform time-series regressions to estimate the betas of RCRD and other factors for each stock, based on an initial estimation period. These estimated betas reflect the exposure of each stock to RCRD and other factors over this period. The first step regression model set up as follows:

$$\begin{aligned} RET_{i,t} = \alpha_i + \beta_{i,RCRD} RCRD_t + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t \\ + \beta_{i,RMW} RMW_t + \beta_{i,CMA} CMA_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Where $RET_{i,t}$ is monthly return of stock i in month t; is the Climate Risk Disclosure factor return in month t; MKT_t is market factor return in month t; SMB_t is size factor (Small Minus Big) in month t; HML_t is book-to-market factor (High Minus Low) in month t; RMW_t is profitability factor (Robust Minus Weak) in month t; CMA_t is investment factor (Conservative Minus Aggressive) in month t; $\varepsilon_{i,t}$ is error term. The betas capture the sensitivity of stock i's returns to each factor.

In the second stage, we use these beta (loadings) estimates as independent variables in cross-sectional regressions to determine their effect on portfolio returns over the following 12 months, allowing us to evaluate the premium associated with each factor, including RCRD. This estimation process is repeated monthly, rolling the estimation window forward until the end of the sample period. The second step regression model set up as follows:

$$\begin{aligned} RET_t = \gamma_{t,0} + \gamma_{t,RCRD}\beta_{RCRD} + \gamma_{t,MKT}\beta_{MKT} + \gamma_{t,SMB}\beta_{SMB} + \gamma_{t,HML}\beta_{HML} \\ +\gamma_{t,RMW}\beta_{RMW} + \gamma_{t,CMA}\beta_{CMA} + \mu_t \end{aligned} \tag{4}$$

Where RET_t is the average return in month t for stocks or portfolios with similar factor loadings; β_{RCRD}, β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA} are factor loadings (betas) estimated in the first stage; $\gamma_{t,0}$ is intercept for the cross-sectional regression; $\gamma_{t,RCRD}$, $\gamma_{t,MKT}$, $\gamma_{t,SMB}$, $\gamma_{t,HML}$, $\gamma_{t,RMW}$, $\gamma_{t,CMA}$ are premiums for each factor in month t; μ_t is error term.

To ensure reliability, we exclude stocks with a survival time shorter than the length of 36 months, thus maintaining consistent beta estimates over time. By using the Fama-MacBeth regression, we can assess whether RCRD offers significant predictive power for future returns and serves as an independent risk factor in the Chinese A-share market.

3.5. Stock Data and Variable Definitions

We obtain monthly stock returns with risk-free rate and quarterly accounting data from the Chinese Stock Market & Accounting Research (CSMAR) database. We classify all A-share stocks into 11 industry sectors, based on the Bloomberg industry classification system, including Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Real Estate, Health Care, Industrials, Materials, Technology, Utilities. Additionally, the monthly market factor (MKT), size factor (SMB), book-to-market factor (HML) and monthly momentum factor (MOM) are also downloaded from CSMAR.

We use a wide range of control variables. ME is firms' market capitalisation. BM is the book-to-market ratio. Ret is the monthly stock return. AGE is the number of years since a stock first appears on the CSMAR database. NI is the net income. DE is the leverage ratio of Ferguson and Shockley (2003). IVA is the investment-to-asset ratio of Lyandres et al. (2008). AG represents the asset growth of Cooper et al. (2008). ACC is the operating accruals of Sloan (1996). ISSUE is the share issuance defined as the logarithm change of outstanding shares over a 1-year period, following Pontiff and Woodgate (2008). A statistical summary of these variables is shown in Table 2.

3.6. Data Sample and Summary Statistics

3.6.1. CRD in Each Year

This CRD captures the extent of a company's climate risk disclosure and its intent in climate risk management. Table 1 presents the percentage of Climate Risk Disclosure (CRD) across different years, summarizing key statistics such as mean, standard deviation, and range from 2002 to 2022. Table 1 provides an overview of how climate risk disclosure practices have evolved over time.

Table 1
Summary Statistics of Climate Risk Disclosure (CRD) by Year
This table reports the summary statistics of CRD across the years from 2002 to 2022.

Yr	N Obs	Mean	Std Dev	Minimum	Maximum
2002	895	0.045	0.049	0.003	0.595
2003	926	0.043	0.046	0.002	0.569
2004	1,015	0.043	0.050	0.002	0.528
2005	635	0.054	0.059	0.003	0.583
2006	1,175	0.055	0.061	0.004	0.634
2007	1,264	0.057	0.067	0.002	1.261
2008	1,371	0.072	0.073	0.001	0.869
2009	1,517	0.081	0.084	0.001	1.254
2010	1,840	0.093	0.099	0.002	1.349
2011	2,121	0.099	0.105	0.002	1.440
2012	2,242	0.119	0.115	0.002	1.391
2013	2,304	0.125	0.116	0.002	1.359
2014	2,426	0.127	0.112	0.002	1.198
2015	2,612	0.152	0.139	0.004	2.611
2016	2,890	0.165	0.151	0.006	2.458
2017	3,266	0.18	0.153	0.002	2.489
2018	3,359	0.197	0.152	0.006	2.820
2019	3,551	0.191	0.145	0.004	2.786
2020	3,935	0.202	0.146	0.014	2.554
2021	4,024	0.227	0.156	0.012	2.439
2022	4,038	0.251	0.163	0.001	2.251

Figure 1 The graph shows the trend of CRD from 2002 to 2022, illustrating the increasing frequency of CRD over time.

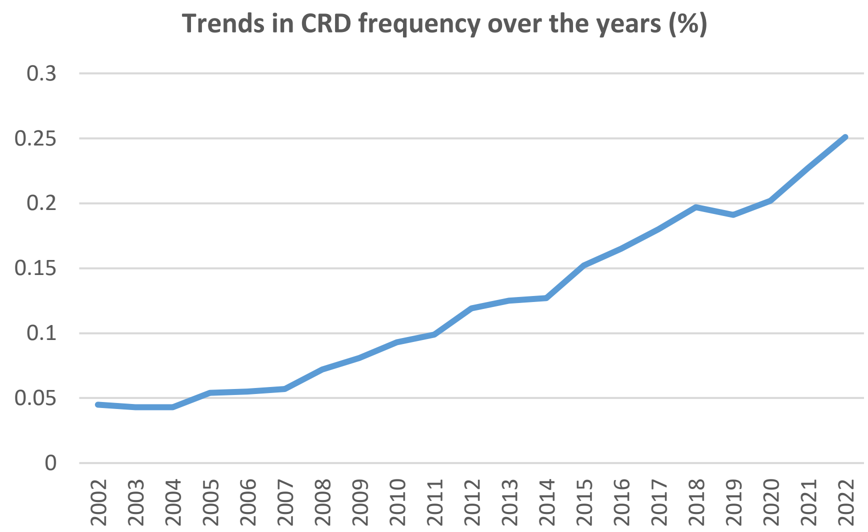


Table 1 presents the summary statistics of Climate Risk Disclosure (CRD) by year, showing how CRD has evolved from 2002 to 2022, including the number of observations, mean, standard deviation, minimum and maximum for each year. The mean CRD value increased from 0.045 in 2002 to 0.251 in 2022, reflecting the increasing importance companies place on climate risk disclosure. A notable point is the significant increase in the maximum CRD value in 2018, reaching 2.489. This change could be driven by several policies. For example, the of the Guidelines for Establishing the Green Financial System issuance in 2016 prompted financial institutions and companies to enhance their climate risk disclosures. Moreover, the implementation of the Environmental Protection Tax Law in 2018 further pressured companies to disclose more information on climate and environmental risks. Additionally, the impact of the Paris Agreement also began to take effect, with Chinese companies significantly increasing climate-related disclosures in response to both international and domestic pressures. These policies contributed to the rapid rise in CRD, reflecting broader and deeper climate risk disclosures in companies' annual reports.

Figure 1 illustrates this upward trend in CRD, visually highlighting the increasing frequency of climate-related disclosures over time. The trend is monotonically increasing, indicating that more companies are disclosing or addressing climate-related risks in their annual reports over time.

3.6.2. CRD in Each Industry

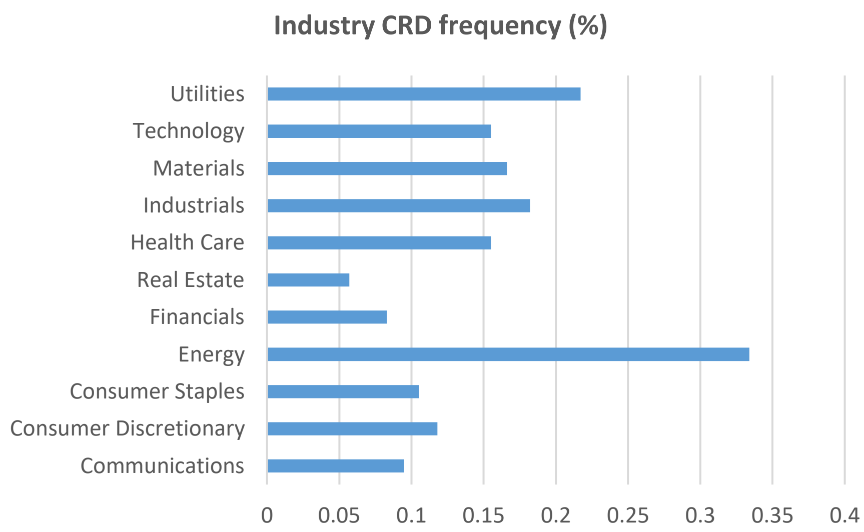
Table 3

Summary Statistics of Climate Risk Disclosure (CRD) in Each Industry

Code	Ind Names	N Obs	Mean	Std Dev	Minimum	Maximum
1	Communications	1734	0.095	0.07	0.003	0.638
2	Consumer Discretionary	7081	0.118	0.104	0.002	1.315
3	Consumer Staples	2822	0.105	0.099	0.002	1.005
4	Energy	1314	0.334	0.324	0.002	1.686
5	Financials	1202	0.083	0.056	0.001	0.463
6	Real Estate	2032	0.057	0.056	0.003	0.904

7	Health Care	4120	0.155	0.101	0.002	0.751
8	Industrials	10926	0.182	0.154	0.001	1.503
9	Materials	8436	0.166	0.131	0.003	1.435
10	Technology	6024	0.155	0.099	0.002	1.345
11	Utilities	1715	0.217	0.26	0.002	2.820

Figure 2 The bar chart displays CRD frequency across industries, indicating the mean CRD for each industry in percentage form.



In Table 3, the CRD (Climate Risk Disclosure) statistics are categorized by 11 industries, following the Bloomberg industry classification. The data reveals that the Energy sector has the highest mean value of CRD at 0.334%, indicating that it has the largest number of companies reporting climate risk in their annual reports of any industry. This finding is consistent with the fact that the energy sector tends to have high carbon emissions and strict environmental regulations which mandatorily require energy firms to disclosure such information. In contrast, the Real Estate sector shows the lowest mean value of CRD, which is 0.057%, reflecting a fewer climate disclosure in that sector, because this industry has a less direct connection to climate-related risks. The maximum CRD value is found in Utilities, with a maximum of 2.82%, suggesting that companies in this sector disclose extensive climate-related information. This is because the utilities industry typically involves energy production and distribution, which are associated with carbon emissions and environmental impacts, leading to stricter regulatory requirements and the need for more climate-related disclosures. The Financials sector, with a mean CRD of 0.083, is relatively low, due to its nature as an office-based industry with limited industrial output and direct environmental impact. However, financial institutions are increasingly focusing on climate risk due to the rise of green finance and ESG investment strategies. As shown in Figure 2, there are differences in CRD percentages across industries, which can be attributed to differences in economic structure and regulatory pressures. For example, Energy and Utilities industries are heavily regulated and directly affected by climate policies, such as emissions reduction and environmental compliance requirements. These sectors also face more critical reviews from investors and regulators. Conversely, sectors like Real Estate and Communications face fewer immediate regulatory pressures and have less direct exposure to environmental impacts, which may explain their relatively lower levels of CRD.

3.6.3 Firm Characteristics

Our data sample includes all China A-share stocks listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), covering the period from December 2002 to December 2022. We collect data from CSMAR database. We use a variety of firm characteristics as control variables in our empirical analysis. Table 2 presents the summary statistics for these variables, including the mean, median, quartiles (Q1 and Q3), and standard deviation.

Table 2
Summary Statistics of Firm Characteristics

This table presents the summary statistics of key financial and firm characteristics, including the mean, median, lower quartile (Q1), upper quartile (Q3), and standard deviation. ME represents market capitalization (in millions), BM is the book-to-market ratio, and RET refers to monthly stock returns. AGE is the number of years since a firm's listing, and CRD (in percent) represents the climate risk disclosure score. NI (in millions) denotes net income, while DE is the leverage ratio, defined as the book value of total liabilities over the market value of equity following Ferguson and Shockley (2003). IVA is the investment-to-asset ratio, calculated as the annual change in gross property, plant, and equipment plus the annual change in inventories, scaled by lagged total assets following Lyandres et al. (2008). AG refers to asset growth following Cooper et al. (2008), and ACC measures operating accruals following Sloan (1996). IVOL captures monthly idiosyncratic volatility of stock returns, measured as the standard deviation of residuals from regressing daily stock returns on the Fama–French three factors, and ISSUE refers to the share issuance measure, defined as the change in the logarithm of shares outstanding over a 12-month period following Pontiff and Woodgate (2008).

		Mean	Median	Q1	Q3	Std Dev
ME	(in millions)	10,543	3,146	1,412	7,073	49,840
BM		0.773	0.569	0.325	0.971	1.094
RET		0.010	-0.004	-0.073	0.073	0.162
AGE		16	16	10	24	9
CRD	(in per cent)	0.153	0.119	0.061	0.195	0.145
NI	(in millions)	598	50	9	179	6177
DE		0.282	0.124	0.035	0.323	0.503
IVA		0.022	0.003	-0.007	0.020	1.261
AG		0.071	0.016	-0.014	0.053	4.366
ACC		0.030	0.004	-0.024	0.032	22.364
IVOL	(in per cent)	0.017	0.016	0.011	0.022	0.008
ISSUE		0.024	0.000	0.000	0.000	0.113

Table 2 presents summary statistics for key financial and firm characteristics, providing insights into the foundational attributes of the sample firms. The Climate Risk Disclosure (CRD) score, in percentage terms, captures the extent of climate-related reporting as the ratio of climate-related keywords to the total word count in a firm's annual report. ME is the Market capitalization, expressed in millions. The book-to-market ratio (BM) is defined as the total equity minus preference shares and minority interests, divided by the market value of tradable shares. Monthly stock return (RET) represents each firm's return for the month. Firm age (AGE) measures the number of years since the firm's first listing in the Chinese A-share market. Net income (NI), in millions, represents the net profit. The leverage ratio (DE) follows the definition of Ferguson and Shockley (2003), calculated as the sum of long-term and short-term loans over the market value of equity. The investment-to-asset ratio (IVA) reflects the annual changes in net fixed assets plus inventories, scaled by lagged total assets, as per Lyandres et al. (2008). Asset growth (AG) is calculated following Cooper et al. (2008) as the change in total assets over the previous year, divided by the lagged total assets. Operating accruals (ACC), following Sloan (1996), are computed by taking the change in current assets (excluding cash equivalents) minus the change in current liabilities (excluding short-term loans and taxes payable), scaled by total assets. Idiosyncratic volatility (IVOL), expressed as a percentage, measures the standard deviation of residuals from regressing daily stock returns on the Fama–French three factors, as per Ang et al. (2006). Lastly, we follow Pontiff and Woodgate (2008) and defined share issuance (ISSUE) as the logarithmic change in adjusted shares outstanding over a 12-month period. These variables provide a comprehensive overview of the financial characteristics of firms, using for exploring the relationship between these characteristics and climate risk disclosures.

4. Results Analyses

This study develops Climate Risk Disclosure (CRD) measures to investigate the relationship between corporate climate disclosures and stock returns by analysing a series of tables (Tables 3-9). We observe the distribution of CRD across industries and stock characteristics grouped by CRD deciles in table 3 and table 4, respectively. We find sector-specific patterns in climate risk reporting and stock characteristics, such as firm age, size, and profitability vary with different levels of climate disclosure. Table 5 serves as a preliminary test, examining raw and abnormal returns across CRD-based groups. Stocks with low CRD exposure have significant higher returns than those with high CRD exposure, indicating higher returns should compensate investors who hold stocks with low degree of climate risk exposure. Building on these findings, we analyse the return predictive power of climate risk exposure in two levels. From the stock-level analysis, we employ fixed effect regression model to directly examine the impact of CRD on stock returns, controlling for firm-specific characteristics. Another is the portfolio level. We form the climate risk exposure portfolio and examines CRD portfolio performance in the following tables. Table 7 compares the mean returns and Sharpe ratios of the climate risk disclosure factor (RCRD) against traditional market factors, highlighting RCRD's standalone risk-adjusted return potential relative to conventional factors. Table 8 evaluates the distinctiveness of RCRD by analysing its relationships with traditional risk factors and policy uncertainty factors, confirming its independence as a unique predictive factor. Finally, Table 9 applies Fama-MacBeth regressions to test RCRD's predictive power for portfolio returns, incorporating traditional and policy factors to validate its robustness across different models.

4.1. Stock Characteristics across CRD deciles

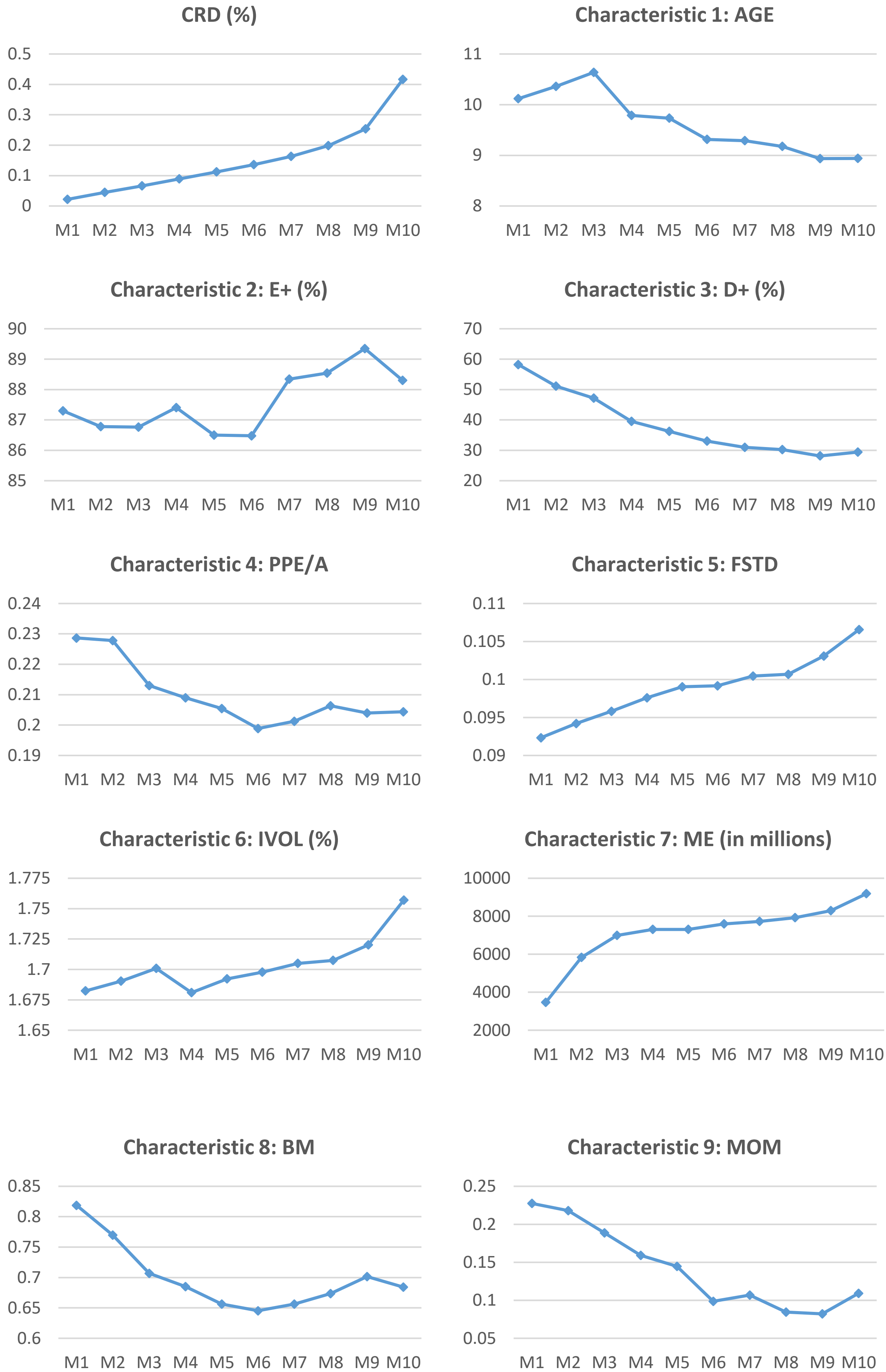
Table 4
Stock characteristics under CRD deciles

This table reports stock characteristics across deciles formed based on the Climate Risk Disclosure (CRD) measure, ranging from M1 (low CRD) to M10 (high CRD). M1 includes the firms with the lowest CRD scores (most undervalued), while M10 contains those with the highest CRD scores (most overvalued). The differences in stock characteristics between M10 and M5, as well as M10 and M1, M5 and M1 are also reported. CRD is the firm's climate risk disclosure score. AGE refers to the number of years since the firm's initial public offering. E+ represents the percentage of firms with positive earnings, and D+ is the percentage of firms paying dividends. PPE/A is the ratio of fixed assets to total assets. ME is the market capitalization, reported in millions. BM is the book-to-market ratio, and MOM represents the stock returns over the past 12 months.

		M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	M10-M1		t-stat.	M10-M5		t-stat.
CRD		0.022	0.044	0.066	0.089	0.112	0.136	0.163	0.198	0.254	0.416	0.394	***	[-836.06]	0.304	***	[-644.84]
AGE		10	10	11	10	10	9	9	9	9	9	-1	***	[28.17]	-1	***	[17.35]
E+	(in per cent)	87.301	86.784	86.766	87.404	86.501	86.480	88.347	88.540	89.348	88.304	1.004	***	[-4.84]	1.803	***	[-8.58]
D+	(in per cent)	58.241	51.118	47.203	39.548	36.255	33.083	30.990	30.219	28.152	29.385	-28.855	***	[95.87]	-6.869	***	[23.15]
PPE/A		0.229	0.228	0.213	0.209	0.205	0.199	0.201	0.206	0.204	0.204	-0.024	***	[23.77]	-0.001		[1.17]
FSTD		0.092	0.094	0.096	0.098	0.099	0.099	0.100	0.101	0.103	0.107	0.014	***	[-44.27]	0.008	***	[-22.62]
IVOL	(in per cent)	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.018	0.001	***	[-12.88]	0.001	***	[-10.5]
ME	(in millions)	3461	5831	6996	7306	7310	7598	7722	7926	8298	9186	5725	***	[-79.18]	1876	***	[-22.28]
BM		0.819	0.770	0.707	0.685	0.656	0.645	0.656	0.673	0.701	0.684	-0.135	***	[38.03]	0.028	***	[-8.89]
MOM		0.227	0.218	0.189	0.159	0.145	0.098	0.107	0.084	0.082	0.109	-0.119	***	[29.44]	-0.036	***	[10.10]

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Figure 3 Characteristics of portfolios formed based on CRD measure



Notes: This figure shows the stock characteristics across deciles based on the climate risk disclosure (CRD) levels. In each year, firms are sorted into deciles according to their CRD measure, from the lowest (M1) to the highest (M10). For each decile, the average values of firm age (AGE), percentage of firms with positive earnings (E+), percentage of dividend payers (D+), the ratio of fixed assets to total assets (PPE/A), standard deviation of analysts' forecasts (FSTD), idiosyncratic volatility (IVOL), market capitalization (ME), book-to-market ratio (BM), and stock returns over the past 12 months (MOM) are calculated.

Table 4 shows the stock characteristics across deciles based on the climate risk disclosure (CRD) levels. In each year, firms are sorted into deciles according to their CRD measure, from the lowest (M1) to the highest (M10). Figure 3 displays the average values of key firm characteristics for each decile, providing insights into how these characteristics vary with climate risk disclosure levels.

CRD values consistently increase from M1 (0.022) to M10 (0.416), confirming that companies in higher deciles report more on climate risk. AGE (years since IPO) shows that firms in the lower CRD deciles tend to be older, with a gradual decrease in age as CRD scores rise. This suggests that younger companies have more willing to disclose climate risks, because young companies are more likely to focus on current environmental expectations, whereas companies with long history are less active in this area. E+ (percentage of firms with positive earnings) shows a slight decrease, from 87.3% in M1 to 80.3% in M10, implying that firms with high CRD scores may have slightly lower earnings, since they have to pay more costs associated with climate risk management. D+ (percentage of firms paying dividends) decreases as CRD deciles increase, from 58.241% in M1 to 29.385% in M10, with a significant difference of -28.855%. This suggests that firms with higher CRD are less likely to pay dividends, as they may reinvest earnings in sustainable projects or climate risk management.

PPE/A (fixed assets to total assets) is the highest in the lowest CRD deciles and decreases slightly as CRD scores increase, suggesting that firms with higher climate disclosure may rely less on fixed assets. FSTD (forecast standard deviation) shows a slight decrease as CRD deciles increase, going from 0.093 in M1 to 0.070 in M10, with a difference of -0.023.

This could suggest that firms with higher CRD scores tend to have lower forecast uncertainty among analysts. This is because more climate risk disclosures provide analysts with additional information to refer to, which helps to reduce the uncertainty in the company's performance. IVOL (idiosyncratic volatility) is mostly stable across these firm characteristics.

ME (market capitalization) declines from 8,361 million in M1 to 575 million in M10, implying that firms with lower CRD scores tend to be larger size. Smaller companies may focus more on climate disclosure to attract environmentally conscious investors. BM (book-to-market ratio) also decreases with higher CRD scores, implying that companies with high CRD have relatively low book-to-market ratios and are typically growth companies. MOM (momentum) declines from 0.227 in M1 to 0.109 in M10, suggesting that low CRD companies have relatively better past performance and may be favoured by traditional investors.

In summary, these figures provide a comprehensive view of how key firm characteristics vary across deciles sorted by climate risk disclosure levels. Firms with high CRD scores are generally younger, smaller. They are less likely to pay dividends and have worse past performance. These firms tend to be valued as growth stocks, with lower book-to-market ratios and more emphasis on climate risk disclosure. Additionally, they may focus more on growth and attracting climate-conscious investors, though they may face slightly more volatility and lower short-term profitability.

4.2. Performance of CRD on Stock Return

4.2.1. Predictive Power Pre-test on sort of CRD

Table 5
Raw return and Alphas based on sort of CRD

This table presents the results of sorting stocks based on Climate Risk Disclosure (CRD) and analysing returns across different groups. In Panel A, stocks are first sorted into deciles based on their CRD scores, with the lowest decile representing firms with the lowest CRD score (indicating minimal climate risk disclosure) and the highest decile representing firms with the highest CRD score (indicating the most extensive disclosure). For each decile, the table reports the average raw returns (Raw Ret) and the abnormal returns (alphas) after controlling for the market factor (CAPM α), the Fama-French three factors (FF3 α), and the Fama-French three factors plus the momentum factor (FF3 + MOM α). The raw returns and alphas are reported in percentages. Additionally, the table provides the return difference (H-L) between the top decile (high CRD score) and the bottom decile (low CRD score) across the different return metrics, along with the corresponding t-statistics (based on Newey-West standard errors) to test the significance of the differences. In Panel B, stocks are first sorted into quintiles based on their market capitalization (Size) or book-to-market ratio (BM) at the end of June each year. Within each Size or BM quintile, stocks are further sorted into three groups based on their CRD score: the top 30% (H), the middle 40% (M), and the bottom 30% (L). The table reports the H-L return difference for each quintile, along with the corresponding t-statistics. The results show how climate risk disclosure impacts stock returns within different Size and BM groups. Significant t-statistics indicate that climate risk disclosure may have a meaningful impact on stock returns, with larger or high-BM firms showing different sensitivities compared to smaller or low-BM firms.

Panel A: Raw returns and alphas of portfolios sorted on CRD

	M1(L)	M2	M3	M4	M5	M6	M7	M8	M9	M10(H)	H-L		t-stat.
Raw RET	1.685	1.688	1.595	1.556	1.454	1.258	1.192	0.982	0.859	1.123	-0.562	***	[-5.19]
CAPM Alpha	1.478	1.478	1.390	1.364	1.281	1.102	1.044	0.842	0.720	0.977	-0.501	***	[-10.67]
FF3 Alpha	1.478	1.477	1.392	1.365	1.283	1.102	1.042	0.841	0.718	0.975	-0.503	***	[-9.38]
FF3 + MOM Alpha	1.552	1.551	1.424	1.345	1.260	1.037	0.942	0.798	0.752	0.963	-0.589	***	[-9.96]

Panel B: Alphas of portfolios sorted first by Size/BM and then on CRD

Size Quintiles	1(S)		2		3		4		5(B)	
Raw ret H-L	-1.209	***	-1.604	***	-1.066	***	-1.038	***	-0.267	**
t-stat.	[-9.32]		[-10.78]		[-9.08]		[-7.97]		[-2.13]	
BM Quintiles	**1(L)**		**2**		**3**		**4**		**5(H)**	
Raw ret H-L	-0.043		-0.912	***	-1.164	***	-1.048	***	-0.675	***
t-stat.	[-0.26]		[-7.01]		[-8.48]		[-9.49]		[-6.25]	

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table 5 presents the raw returns and abnormal returns (alphas) for portfolios sorted by Climate Risk Disclosure (CRD) levels. This table provides a preliminary assessment of the potential return predictive power of CRD, serving as a foundation for the subsequent Fama-MacBeth regression analysis. The analysis is divided into two panels:

In Panel A, stocks are sorted into deciles based on their CRD scores, from the lowest decile (M1, representing firms with minimal climate risk exposure) to the highest decile (M10, representing firms with maximum climate risk exposure). The raw return (Raw RET) and alphas adjusted by different risk models are reported for each decile, with the differences between the top decile (M10) and bottom decile (M1).

The raw returns decrease from M1 (1.685%) to M10 (1.123%), with a difference of -0.562% between M10 and M1. The significant negative difference of H-L suggests that firms with high CRD tend to yield lower raw returns than those with low CRD, indicating a strong return predictive ability on CRD. This finding is consistent with the fact that higher risk programme should compensate more premium to investors who tolerate the risk that firms minimally disclose climate information to the public, vice versa. The CAPM alpha also shows a decreasing trend across CRD deciles, from 1.478% in M1 to 0.977% in M10, with a significant difference of -0.501% between M10 and M1. This finding shows that the predictive power of CRD on stock returns are not solely explained by market exposure. When controlling for the Fama-French three factors, the alpha decreases from 1.478% in M1 to 0.975% in M10, showing a significant H-L difference of -0.503%. After adjusting for the Fama-French three factors and momentum factor, the alpha decreases from 1.552% in M1 to 0.963% in M10, with a significant difference of -0.589%. The trend remains after adjusting for size and book-to-market effects. These consistent results further support that our findings.

Panel B examines whether the return predictive power of CRD is influenced by Size and Book-to-Market (BM) characteristics. Stocks are first sorted into quintiles based on either market capitalization (Size) or book-to-market ratio (BM) at the end of each year. Within each Size or BM quintile, stocks are further divided into three groups by CRD score: the top 30% (H), middle 40% (M), and bottom 30% (L). The H-L difference in returns within each quintile is reported to assess the consistency of CRD's predictive ability across Size and BM.

In the Size quintiles, the H-L return difference is significantly negative across all quintiles, with values ranging from -1.066% in the smallest quintile to -0.267% in the largest quintile. These significant results suggest that the relationship between CRD and returns is not merely due to firm size, as the negative H-L differences are consistent across all Size groups. Similarly, in the BM quintiles[2], the H-L return difference is also significantly negative, ranging from -1.048% to -0.043%, with the strongest effect in the middle BM groups. This suggests that the predictive relevance of CRD on returns is not subsumed by the book-to-market effect, as the H-L differences remain negative and significant across all BM quintiles.

Overall, Table 5 suggests that CRD may have predictive ability for stock returns. Panel A shows that portfolios with low CRD scores generally outperform those with high CRD scores, with this trend holding across various conventional variables. Panel B confirms that this relationship remains robust across different firm sizes and book-to-market ratios, indicating that the association between CRD and returns is not solely driven by Size or BM effects. These findings suggest that CRD may serve as a meaningful factor in stock return analysis, potentially enabling investors to identify high abnormal returns by focusing on firms with lower CRD levels.

4.2.2. Fixed-Effects Panel Regressions

[2] We observe an insignificant value of H-L difference in the small BM quantile. To rule out a potential influence of BM on the return predictive power of CRD, we include BM as a control variable on the following regressions analysis.

Table 6

CRD and Stock Returns: Fixed-Effects Panel Regressions

This table reports the results of fixed-effects panel regressions of monthly stock returns (RET) on Climate Risk Disclosure (CRD) and other control variables. Model 1 shows the regression of RET on CRD alone. Models 2 through 9 incrementally add control variables, including firm size (LOGME), book-to-market ratio (LOGBM), past returns (RET_{t-1} and $\mathrm{RET}_{t-12,t-2}$), stock issuance (ISSUE), idiosyncratic volatility (IVOL), accruals (ACC), asset growth (AG), investment-to-assets (IVA), and leverage ratio (DE). All models account for heteroskedasticity and clustering. The reported R^2 and the number of observations is listed at the bottom of each column.

	1	2	3	4	5	6	7	8	9
Intercept	-0.061 ***	0.752 ***	0.669 ***	0.403 ***	0.770 ***	0.753 ***	0.765 ***	-0.144 ***	-0.225 ***
	[-53.80]	[23.57]	[24.03]	[13.59]	[23.60]	[23.66]	[23.39]	[-24.85]	[-40.19]
CRD	-0.037 ***	-0.050 ***	-0.049 ***	-0.049 ***	-0.050 ***	-0.050 ***	-0.051 ***	-0.023 ***	-0.034 ***
	[-8.09]	[-5.26]	[-5.70]	[-6.83]	[-4.92]	[-5.26]	[-5.21]	[-3.89]	[-5.99]
LOGME		-0.002 ***	-0.001	0.000	-0.002 **	-0.002 ***	-0.002 **	0.013 ***	0.010 ***
		[-2.60]	[-0.94]	[-0.69]	[-2.49]	[-2.64]	[-2.45]	[18.43]	[16.39]
LOGBM		-0.730 ***	-0.669 ***	-0.452 ***	-0.746 ***	-0.731 ***	-0.744 ***	-0.048 ***	-0.031 ***
		[-32.36]	[-33.56]	[-22.03]	[-32.22]	[-32.53]	[-32.39]	[-34.96]	[-29.98]
RET_{t-1}		-0.001	-0.001	-0.046 ***	0.000	-0.001	-0.001	-0.002	-0.047 ***
		[-0.44]	[-0.37]	[-13.84]	[0.23]	[-0.47]	[-0.44]	[-0.91]	[-8.22]
$\mathrm{RET}_{t-12,t-2}$		-0.008 ***	-0.007 ***	-0.016 ***	-0.008 ***	-0.008 ***	-0.009 ***	-0.013 ***	-0.020 ***
		[-12.57]	[-12.81]	[-15.56]	[-13.58]	[-13.03]	[-14.43]	[-15.49]	[-18.39]
ISSUE			0.025 ***						-0.014 ***
			[11.46]						[-4.93]
IVOL				5.396 ***					5.245 ***
				[88.35]					[91.98]
ACC					0.019 ***				0.015 ***
					[3.84]				[3.08]
AG						0.000			0.000
						[1.02]			[0.76]
IVA							0.000		0.000

							[0.61]		[-0.55]
DE								0.004 ***	0.002 *
								[4.47]	[1.87]
R^2 (%)	0.61	2.05	2.20	8.04	2.18	2.06	2.11	3.16	10.08
Obs.	566,206	518,224	512,521	390,373	456,508	518,136	507,268	361,203	317,892

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table 6 presents the results of fixed-effects panel regressions analysing the relationship between monthly stock returns (RET) and Climate Risk Disclosure (CRD), along with various control variables. In this table, we regress stock returns on CRD alone. We then add control variables: firm size (LOGME), book-to-market ratio (LOGBM), past returns (RET_{t-1} and $\mathrm{RET}_{t-12,t-2}$), stock issuance (ISSUE), idiosyncratic volatility (IVOL), accruals (ACC), asset growth (AG), investment-to-assets (IVA), and leverage ratio (DE) in sequence from models 2 to 9. This horse race approach allows us to observe the incremental impact of each control variable on the relationship between CRD and returns.

Across all models, the coefficients on CRD are consistently negative and statistically significant. Specifically, the coefficient on CRD in model 1 is -0.037, suggesting that firms with extensive climate exposure does not compensate investors higher returns than those choose to minimally disclose. Another possible explanation is that investors might view high climate risk disclosure as a signal that companies are facing potential challenges related to environmental risks, regulatory compliance, or resource allocation toward sustainability initiatives. These factors could lead to increased costs or reduced short-term profitability, making high-CRD firms less attractive from an investment perspective. This finding is consistent with the result of Table 5 where we observe a significantly negative raw (abnormal) returns between the H-L CRD differences. This negative relationship persists from Models 2 through 9, with the CRD's coefficients ranging from -0.030 to -0.050. This suggests a robust relationship that firm climate risk disclosure (CRD) is negatively impact on stock returns.

Additionally, the coefficient on LOGME is generally negative and significant in most regressions, indicating that larger firms tend to have lower returns. This result aligns with the standard finding in finance that smaller firms typically have higher returns, as reaffirmed by Fama and French (2008), who documented the persistence of the size effect, where small-cap firms earn higher average returns than large-cap firms. LOGBM consistently shows a significant negative coefficient, suggesting that firms with a higher book-to-market ratio tend to have lower returns in this context, since they often been considered as value stocks. This aligns with findings from Chui, Titman, and Wei (2010), who noted that in emerging markets, growth stocks (low B/M) might achieve higher returns due to greater risk tolerance or expectations among investors, consistent with the observed lower returns for high B/M (value) stocks. Both recent past returns (RET_{t-1}) and past returns over a 12-month horizon ($\mathrm{RET}_{t-12,t-2}$) have negative coefficients. This suggests that there is a slight return reversal effect, where past returns negatively predict future returns, especially over a longer horizon. This is consistent with Jegadeesh and Titman (2001), who identified a reversal effect in short-term returns, further supporting the notion of mean reversion in stock prices over specific time periods.

The coefficient on ISSUE is positive and significant in Model 3&9, indicating that firms with higher stock issuance tend to have higher future returns. This finding aligns with the research by Carlson, Fisher, and Giammarino (2006), who propose that firms issue equity to finance growth opportunities, leading to positive market reactions and higher subsequent returns. The positive and significant coefficient on IVOL in Models 4 and 9 indicates that higher idiosyncratic volatility is associated with higher expected returns. This is consistent with the study by Fu (2009), which demonstrates that stocks with higher idiosyncratic volatility exhibit higher expected returns, suggesting that investors require additional compensation for bearing increased firm-specific risk.

So far, we have analysed the relationship between the climate risk exposure and stock returns. We find that the return predictive ability of climate risk exposure in stock level. In Section 4, we move to the portfolio level by forming a climate risk exposure factor, denoted as the RCRD. Section 4 investigates whether the loadings on RCRD could predict future portfolio returns.

4.3 Performance of CRD Portfolio Return on Future Stock Return

To further explore the implications of climate risk disclosures, we construct the Climate Risk Disclosure factor (RCRD), defined as the return spread between portfolios with low and high CRD deciles. RCRD represents a zero-investment strategy that goes long on firms with minimal disclosures and shorts firms with extensive disclosures, capturing the pricing effects of climate disclosure discrepancies. Building on the observed link between CRD and stock returns, RCRD provides a systematic framework to evaluate the financial relevance of climate transparency. By isolating the return premium associated with climate risk disclosure levels, RCRD enriches the understanding of stock anomalies and offers novel insights into how climate risk related information shapes asset pricing.

4.3.1. The comparison between RCRD Performance and Fama-French Factors

Table 7
Performance Summary of factors

This table shows the performance of CRD-based factors and traditional risk factors, including market factor (MKT), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), and investment factor (CMA). RCRD represents the overall return spread between firms with high and low levels of climate risk disclosure. Mean ret shows the average monthly excess return for each factor, calculated relative to the risk-free rate. t-stat is the t-statistic associated with the mean return, indicating the statistical significance of each factor's return. Sharpe ratio measures the risk-adjusted return by dividing the mean return by its standard deviation. Positive % reports the percentage of months where the factor generated a positive return.

	Mean ret		t-stat.	Sharpe ratio	Positive %
RCRD	0.619	**	[2.04]	0.130	54.07
MKT	0.532		[1.12]	0.071	53.66
SMB	0.620	**	[2.02]	0.129	52.03
HML	-0.009		[-0.04]	-0.003	49.59
RMW	-0.039		[-0.19]	-0.012	49.59
CMA	0.048		[0.32]	0.020	50.41

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table 7 shows a statistics summary of the Climate Risk Disclosure-based factor (RCRD) alongside traditional risk factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), and investment factor (CMA). RCRD represents the return spread between firms with high and low levels of climate risk disclosure, calculated as the difference in returns between the top decile and bottom decile of firms ranked by their CRD levels. Specifically, the top decile consists of firms with the highest levels of climate risk disclosure, while the bottom decile includes firms with the lowest levels. Each factor's performance is evaluated in terms of mean excess return, t-statistic, Sharpe ratio, and the percentage of months with positive returns.

The mean return of RCRD is 0.62%, with a t-statistic of 2.04. This mean return is the highest among the factors, with only SMB showing a comparable mean return of 0.62% (t=2.02). With a Sharpe ratio of 0.130, RCRD outperforms all other factors, including MKT (0.071), SMB (0.129), and others, demonstrating that it provides the highest risk-adjusted return among the factors. This high Sharpe ratio highlights the effectiveness of RCRD in capturing returns relative to its risk, suggesting that climate risk disclosure may offer unique return opportunities. In summary, Table 7 suggests that RCRD outperforms traditional factors in terms of both mean return and risk-adjusted return, indicating climate risk exposure has the return predictive power. This finding is consistent with the one of Table 5 and Table 6.

4.3.2. Relationship between RCRD and other factors

Table 8
Relationship between RCRD and other factors

This table presents the relationship between the Climate Risk Disclosure factor (RCRD) and other market and policy factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), investment factor (CMA), Economic Policy Uncertainty (EPU), and Climate Policy Uncertainty (CPU). Policy factor EPU is computed as the difference in the natural logarithm of Economic Policy Uncertainty values between the current and previous month. Similarly, factor CPU is derived as the yearly log difference, capturing the annual change in climate policy uncertainty by calculating the difference between the current year’s log Climate Policy

Uncertainty and the log value of the previous year. Panel A presents Pearson correlation coefficients between RCRD and other factors. Panel B reports the results of OLS regressions of RCRD on other risk factors. Model 1 uses the CAPM framework. Model 2 extends it to the Fama-French 3-factor model. Model 3 further expands to the Fama-French 5-factor model. Model 8 incorporates policy variables into the 5-factor model to assess the impact of economic and climate policy uncertainties on returns.

Panel A: Pearson correlation among factors

	RCRD	MKT	SMB	HML	RMW	CMA	EPU
MKT	0.255						
SMB	0.273	0.117					
HML	0.013	-0.162	-0.559				
RMW	-0.405	-0.280	-0.745	0.287			
CMA	0.404	0.092	0.381	0.120	-0.676		
EPU	0.006	-0.143	-0.095	0.140	0.079	0.062	
CPU	0.063	0.076	0.065	-0.052	-0.027	0.077	0.000

Panel B: Regression of RCRD on other factors

	1		2		3		8	
Intercept	0.033	***	0.026	***	0.021	***	0.020	**
	[39.39]		[10.62]		[7.01]		[2.18]	
MKT	0.116	**	0.115	**	0.085		0.086	
	[2.00]		[2.15]		[1.64]		[1.64]	
SMB			0.417	***	0.150		0.151	
			[3.42]		[1.22]		[1.17]	
HML			0.406	***	0.211	*	0.211	*
			[2.83]		[1.71]		[1.70]	
RMW					-0.245		-0.245	
					[-1.47]		[-1.43]	
CMA					0.412	**	0.410	**
					[2.37]		[2.33]	
EPU							0.002	
							[0.15]	
CPU							-0.002	
							[-0.08]	
R^2 (%)	0.1905		0.3066		0.3601		0.3601	
Obs.	246		246		246		246	

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table 8 examines the relationship between the Climate Risk Disclosure factor (RCRD) and other market and policy factors, including the market factor (MKT), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), investment factor (CMA), and two macroeconomic factors: Economic Policy Uncertainty (EPU) and Climate Policy Uncertainty (CPU). The table is divided into two panels: Panel A presents Pearson correlation coefficients among the factors. Panel B reports the regression results of RCRD on these factors.

In Panel A, the correlations between RCRD and other factors are generally low, indicating weak associations across all factors. This result suggests that RCRD may capture information distinct from conventional market and policy factors, supporting its uniqueness as a factor that offers insights beyond these established variables.

In Panel B, the regression results further emphasize RCRD's independence from other factors. Across all models, the intercept remains positive and statistically significant, suggests that RCRD contains unique information which is not accounted for by the other factors. In Model 2, MKT and SMB show significant positive coefficients. HML remains significant across regressions, and CMA is consistently positive and significant in Models 3 and 4, indicating that traditional factors explain some variation in RCRD, but they do not fully capture its information. When the policy factors EPU and CPU are added in Model 4, the significantly positive intercept remains, suggesting that economic and climate policy uncertainties do not rule out the information of RCRD.

4.3.3. Fama-Macbeth Regression

Table 9
Predictive Power of factors on portfolio level

This table reports the results of the Fama-MacBeth regression of the monthly excess returns on portfolios constructed based on various factors including climate-related disclosure factor (RCRD), market factor (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and macroeconomic factors Economic Policy Uncertainty (EPU) and Climate Policy Uncertainty (CPU). The regression estimates the loadings of portfolio returns on these factors, using monthly portfolio-level data from 2002 to 2022. Each column represents a different model specification, introducing or omitting certain factors to test the robustness of the results. The reported coefficients are the time-series averages of the factor loadings from the cross-sectional regressions. The Newey-West standard errors with 12-month lags are used to adjust for heteroscedasticity and autocorrelation in the error terms.

	(1)		(2)		(3)		(4)		(5)	
Intercept	0.019	***	0.016	***	0.020	***	0.034	***	0.006	
	[18.11]		[10.00]		[11.74]		[8.48]		[1.23]	
β_{RCRD}			0.011	*	0.024	**	0.045	***	0.059	***
			[1.86]		[2.06]		[4.27]		[5.03]	
β_{MKT}	-0.009	**			-0.020	***	0.001		-0.057	***
	[-2.03]				[-4.80]		[0.13]		[-4.51]	
β_{SMB}	-0.011	**			-0.009		-0.034	***	-0.015	**
	[-2.42]				[-1.63]		[-3.88]		[-2.38]	
β_{HML}	0.004				0.008		0.020	***	-0.022	***
	[0.52]				[0.88]		[2.75]		[-4.88]	
β_{RMW}							-0.021	***	-0.005	**
							[-4.33]		[-2.51]	
β_{CMA}							0.023	***	0.016	***
							[3.88]		[3.92]	
β_{EPU}									0.190	***
									[10.96]	
β_{CPU}									0.145	***
									[9.21]	
Adj_R^2 (%)	29.48		10.85		33.88		42.94		42.08	
No. obs.	5850		5850		5850		5850		5850	

Notes: * Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

Table 9 presents the results of Fama-MacBeth regressions on monthly excess portfolios returns with the Climate Risk Disclosure factor (RCRD) and other variables such as market (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and two policy factors: Economic Policy Uncertainty (EPU), and Climate Policy Uncertainty (CPU). Each regression incrementally introduces new factors, allowing an examination of the predictive power of RCRD both independently and in combination with these additional variables.

In Regression 1, we start with the Fama-French three-factor model, incorporating MKT, SMB, and HML as the primary predictors of portfolio returns. MKT and SMB are both significant and negatively associated with portfolio returns. Regression 2 isolates the effect of RCRD by including only β_{RCRD} as the predictor. The premium of RCRD in this regression is 0.011 with a t-value of 1.86, which is positive and significant, indicating that loadings on climate risk disclosure can positively forecast future portfolio returns. This result suggests that the market values transparency in climate-related disclosures, and firms with greater climate risk disclosure tend to achieve higher returns as investors respond positively to their improved transparency. In Regression 3, RCRD is added to the Fama-French three-factor model (MKT, SMB, HML), allowing us to test whether its predictive power persists alongside traditional factors. The coefficient for β_RCRD remains positive and significant (0.024, t = 2.06), demonstrating that RCRD provides unique information for return predictability beyond what is explained by market, size, and value factors. This is further supported by an increase in the adjusted R^2, highlighting the model's improved explanatory power. Regression 4 extends the analysis by incorporating the Fama-French five-factor model, which includes RMW (profitability) and CMA (investment). The coefficient for β_RCRD increases to 0.045 (t = 4.27), remaining strongly significant and reinforcing the conclusion that RCRD offers unique insights into return predictability. Additionally, RMW is negatively significant, and CMA is positively significant, further enriching the model's explanatory scope. Regression 5 builds upon this framework by introducing policy-related factors, EPU (Economic Policy Uncertainty) and CPU (Climate Policy Uncertainty), which capture the impact of macroeconomic and climate policy uncertainties. Even with these additions, β_RCRD remains positive and highly significant (0.059, t = 5.03), underscoring its robustness. Both EPU and CPU are also significant, indicating their relevance in explaining return variations. The adjusted R^2 of the final model reaches 42.08%, reflecting enhanced explanatory capability with the integration of traditional risk, firm-specific, and policy-related factors.

In summary, as we progress through each regression model, we observe that the premium of RCRD consistently maintains a positive and significant coefficient, underscoring its strong predictive power for portfolio returns. The incremental addition of factors improves the model's explanatory power, as reflected by the increasing adjusted R^2 across models. This result suggests that while traditional and policy-related factors contribute to explaining return variations, RCRD remains as a valuable independent predictor of portfolio returns.

This study develops and examines Climate Risk Disclosure (CRD) measures to investigate the relationship between corporate climate disclosures and stock returns by systematically analysing a series of tables (Tables 3-9). Table 3 explores the distribution of CRD across industries, revealing sector-specific patterns in climate risk reporting. Table 4 provides stock characteristics grouped by CRD deciles, illustrating how variables such as firm age, size, and profitability vary with levels of climate disclosure. Table 5 serves as a preliminary test, examining raw and abnormal returns across CRD-based groups to assess potential links between disclosure levels and stock returns. Building on this, Table 6 employs regression analysis to isolate the direct impact of CRD on returns, controlling for firm-specific characteristics. Table 7 compares the mean returns and Sharpe ratios of the climate risk disclosure factor (RCRD) against traditional market factors, highlighting RCRD's standalone risk-adjusted return potential relative to conventional factors. Table 8 evaluates the distinctiveness of RCRD by analysing its relationships with traditional risk factors and policy uncertainty factors, confirming its independence as a unique predictive factor. Finally, Table 9 applies Fama-MacBeth regressions to test RCRD's predictive power for portfolio returns, incorporating traditional and policy factors to validate its robustness across different models. The consistent significance of RCRD across regression models reinforces its role as a stock anomaly. This finding highlights RCRD's ability to capture unique risks associated with climate disclosures, distinguishing it from traditional risk factors in asset pricing.

5. Conclusion

This essay explores the relationship between Climate Risk Disclosure (CRD) and stock return anomalies in the Chinese A-share market. There are several key findings.

Firstly, we construct a robust firm-level CRD measure using textual analysis of corporate annual reports. With quantifying climate-related disclosures through a lexicon of 155 keywords derived from authoritative sources, this measure captures firms' willingness to voluntarily disclose and manage climate risks. Our descriptive analysis reveals significant variations in CRD across industries and firm characteristics, with distinct patterns in size, profitability, and firm age among corporates with different levels of climate transparency. This finding reflects the variability in climate disclosure practices among companies in the Chinese stock market.

Secondly, we investigate the relationship between CRD and stock returns at both stock-level and portfolio-level analyses. Our results indicate that firms with lower CRD scores tend to deliver higher subsequent returns, suggesting a potential risk premium demanded by investors for holding stocks with low climate disclosure. This relationship is further validated through the construction of a climate risk exposure factor (RCRD), where portfolios formed by longing low-CRD decile stocks and shorting high-CRD decile stocks yield significant abnormal returns. These findings emphasize the return predictive power of climate risk exposure in identifying stock return anomalies.

Thirdly, the results of Fama-MacBeth regressions confirm the robustness of RCRD as a validate factor. Loadings on RCRD factor are positively and significantly associated with future portfolio returns, indicating that climate risk-related information embedded in RCRD is underutilized by Chinese investors, and therefore not fully incorporated into asset prices. We argue that RCRD can qualify as a stock anomaly in the Chinese stock market, in which previous literature do not find. .

In summary, this paper demonstrates that climate risk disclosure is a significant determinant of stock return anomalies in the Chinese A-share market. The findings provide robust empirical evidence on the role of climate transparency in influencing market efficiency and investment strategies. By highlighting the predictive power of CRD, this study contributes to the broader literature on climate finance and asset pricing, offering new insights into the unique dynamics of developing markets. Future research could expand on these findings by exploring the interaction between CRD and other market anomalies, or by examining how regulatory changes further shape climate disclosure practices and their impact on financial markets.

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