

'E' of ESG and Firm Performance: Evidence from China

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Abstract

Following the ESG rating divergence reported in the previous research studies, we develop a novel firm-level Green Commitment (GC) index by incorporating new dimensions of environmental management and governance. We construct GC scores for all A-share listed companies in China from 2015 to 2021 and analyze whether firms with greater environmental commitment exhibit improvements in their future performance. Our results show that firms with high GC scores achieve higher stock returns without incurring extra risk. Additionally, a strong environmental commitment can enhance operating performance by mitigating financial constraints. The evidence supports the view that environmental investing contributes to the creation of positive shareholder value. Our GC index can be applied more widely to resolve the mixed evidence on the value implications of corporate environmental commitments.

Keywords: Environmental investing, ESG divergence, Firm performance, Financial constraints, Industry competition, State ownership

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1. Introduction

The extant literature lacks consensus on whether shareholders benefit from a firm's investments in improving its environmental performance (Gillan et al., 2021). One strand of research suggests that firms enhance their corporate reputation by adopting environment friendly practices, ultimately bolstering their social standings and delivering long-term value (Boubakri et al., 2016; Cai et al., 2020; Garel & Petit-Romec, 2021). The value addition is created through environmental strategies for product differentiation, effectively signaling a firm's commitment to social welfare, and conveying the superiority of product or service quality to target customers (Albuquerque et al., 2019; Bénabou & Tirole, 2010; Noor et al., 2020). Moreover, environmental commitment enables managers to cater to investors' preferences and mitigate information asymmetry between firms and stakeholders, thereby overcoming invisible financing barriers and improving operating efficiency (Dhaliwal et al., 2011; Houston & Shan, 2022; Lian et al., 2023).

Contrary to the above, another strand of research suggests that increased spending on environmental initiatives may not always align with shareholders' interests. Such initiatives demand sustained commitment of financial resources, potentially at the expense of forsaking profitable but unsustainable investments (Baker et al., 2022; Blitz & Fabozzi, 2017; Bolton & Kacperczyk, 2021; Hong & Kacperczyk, 2009; Sam & Zhang, 2020). A survey of institutional investors conducted by Eccles et al. (2017) reveals that more than a third of respondents believe that Environmental, Social and Governance (ESG) investing diminishes shareholder value.

The lack of consensus regarding the value creation through environmental investing in previous studies could be due to divergence in the ESG ratings. Evaluation of a firm's ESG performance requires rating agencies to exercise judgment, leading to disparities in rating scores across providers (Berg et al., 2022). Recent empirical studies have highlighted substantial disagreements in ESG ratings in China, and how they negatively affect stock returns (Wang et al., 2024; Xiao et al., 2023). Wang & Liu (2024) find that ESG rating divergence is positively correlated with greater ESG disclosures for Chinese firms issuing green bonds. Their evidence suggests that ESG ratings do not accurately

reflect the true value of ESG disclosure information. This highlights the need for developing a more reliable measure of firm's environmental performance.

This paper investigates the association between environmental performance and shareholder value by developing a comprehensive firm-level Green Commitment (GC) index for all Chinese listed companies. The GC index comprises 20 firm-level indicators across six environmental categories, covering a broad range of issues such as environmental management, protection, disclosure, and governance. Each environmental indicator is represented as a dummy variable and is equally weighted, addressing the subjective bias identified in ESG ratings identified by Berg et al. (2022). Our analysis reveals that companies with high GC scores achieve higher stock returns without incurring additional risks.

We further explore how firms with increased environmental commitment create shareholder value. We argue that one way a firm's environmental commitment can increase shareholder value is by providing external creditors with firm-specific information to mitigate external financial constraints. We analyze this proposition and find that firms with high GC scores experience improved operating performance that could be attributed to reduction in financial constraints.

Further, previous evidence indicates that firms operating in a highly competitive environment (e.g., Bernini & Montagnoli, 2017) and those that are not state owned (e.g. Poncet et al., 2010) face higher levels of financial constraints. Thus, we conduct additional analyses to examine whether the impact of green commitment on shareholder value varies with the level of competition and ownership structure. Our findings reveal a positive association between GC scores and operating performance for firms operating in highly competitive environment and Non-State-Owned Enterprises (Non-SOEs). The findings suggest firms that are free from government control and face high competition can benefit their shareholders through greater environmental commitments

Our study contributes to the existing literature in several ways. First, we propose an innovative approach for measuring firm-level environmental performance by building a comprehensive GC index. We consider several dimensions that reflect the green

commitment of firms including the presence of an environmental management system, pro-environmental human resource management, disclosures about green spending and environmental protection performance, the credibility of these disclosures, and the effectiveness of environmental governance. As far as we are aware, this is the first study to propose a GC index based on a comprehensive set of measures. Second, our findings demonstrate that environment commitment can enhance shareholder value. We confirm that environment commitment can improve operating performance by mitigating financial constraints. Finally, our study enriches the academic discourse on the benefits of environmental investing, providing valuable insights for managers, policymakers, and investors. For managers, the implication is that environmental engagement can alleviate financial constraints. Policymakers can incentivize firms to increase their environmental commitments, thereby advancing progress towards a low-carbon economy. Environmentally conscious investors can use our GC index scores to make more informed investment decisions.

The rest of the paper is organized as follows. Section 2 explains the theoretical framework and discusses relevant literature. Section 3 provides details of how we construct our unique data set and methods used for analysis. Section 4 presents and discusses the empirical results. Section 5 conducts robustness check. Finally, Section 6 concludes.

2. Theory and Literature

2.1 Environmental performance and shareholder value

The shareholder wealth maximization theory suggests that a firm's primary objective should be to maximize its owner's wealth (Jensen & Meckling, 1976). Shareholders bear substantial risk by providing capital, and thus, managers should strive to increase the shareholder value over time. The theory instructs efficient use of scarce capital, as failure to meet shareholder expectations may lead them to sell their stakes and seek better returns elsewhere. Thus, the shareholder wealth maximization approach has been a well-accepted framework for assessing the value that a firm generates for its owners (Dobson, 1999; Harris & Raviv, 2010; Hart & Zingales, 2017; Jensen, 2001).

However, the exclusive focus on shareholder wealth maximization can potentially lead

managers to prioritize profit-making ventures at the expense of broader societal considerations. According to the stakeholder theory (Freeman et al., 2010, 2021), a firm should be perceived as a governance mechanism facilitating a series of contracts among stakeholders, each benefiting economically from their relationships. Increasing concerns over environmental degradation have led to greater scrutiny corporate environmental, social, and governance (ESG) practices. Good ESG performance can help firms secure new resources, build a positive corporate culture, and enhance both internal and external effectiveness (Branco & Rodrigues, 2006; Su & Xue, 2024). As a consequence, environmental initiatives and their voluntary disclosures are increasingly used by firms to signal their commitments to sustainability (Fombrun, 2005; Chapple & Moon, 2005; Stubbs et al., 2013).

There is mix evidence reported in the literature regarding the relationship between environmental performance and firm value. Some studies suggest that social responsibility initiatives may come at the cost of firm value. For instance, Di Giuli & Kostovetsky (2014) report a negative association between CSR ratings and both short and long-term firm performance of large U.S. companies. Further, Ciciretti et al. (2023) show that firms with high ESG scores measured by Refinitiv ASSET4, exhibit lower expected returns across a global sample of 7,772 companies. Sam & Zhang (2020) find a huge decline in the market values (approx. \$29bn) of high polluting industry firms following the announcement and stricter environmental regulations in China.

Contrary to the above, another stream of research provides evidence of positive impact of environmental engagement on firm value. For example, Garel & Petit-Romec (2021) show that companies with responsible environmental strategies experienced better stock returns during the COVID-19 pandemic, as investors increasingly prioritized environmental concerns. Wen et al. (2022) also find that higher ESG disclosure quality scores from Sustainalytics improve Tobin's Q, ROA, and reduced downside risks. Chen et al. (2023) develop a composite firm-level ESG scoring system and find that stocks with high ESG scores outperform those with low ESG scores in the Chinese A-share stock markets.

2.2 Environmental performance measurement

Mixed evidence on the shareholders benefits of environmental performance could be due to divergence in ESG ratings (Gillan et al., 2021). The evaluation of a firm's ESG performance is influenced by rating agency's subjective judgment that could cause inconsistencies in ratings across providers (Berg et al., 2022; Wang et al., 2024). Berg et al. (2022) suggest that the divergence of rating scores for the same ESG attribute creates a "rater effect", which can account for 15% of the variation in scores for a particular ESG category.

Variability in measurement of environmental performance carries significant implications. When ESG ratings vary, investors may interpret the data differently, leading to diverse expectations about a company's future value. The uncertainty arising from ESG rating divergence can cause discrepancies between stock market prices and intrinsic values, leading to inefficient pricing (Brandon et al., 2021; Serafeim & Yoon, 2023; Wang et al., 2024).

In the context of China, variations in ESG ratings present greater challenges for several reasons. Firstly, environment-related information used by both ESG rating agencies and previous research studies often relies on company disclosures. However, firms frequently disclose information about ESG voluntarily and without strong commitment. Consequently, such disclosures can be prone to upside bias and are sometimes perceived as self-laudatory or "greenwashing" (Liao et al., 2023). For instance, Zhang (2023) highlights that Chinese firms impacted by the "low carbon city" pilot policy tend to engage in symbolic speech and selectively disclose positive CSR information, while taking few substantive actions to genuinely reduce carbon emissions.

Secondly, ESG rating agencies cover relatively limited number of Chinese companies. In China, the ESG ratings are available for less than half of all A-share listed companies (Chen et al., 2023). Consequently, evidence based on ESG ratings cannot be reliable due to lack of a comprehensive coverage. This may lead to the mixed evidence reported in previous studies on China. For example, Ni & Sun (2023) assess ESG performance of 554 Chinese firms with rating scores available from the Refinitiv ESG database for the period 2016-2021 and find that firms with lower ESG scores achieve higher stock returns. In contrast, Zhang et al. (2022) utilize Bloomberg's ESG disclosure scores for

Chinese listed firms and find that both high- and low-level ESG portfolios earn abnormal returns. Notably, the number of firms with ESG scores in their sample, varies from 90 in 2005 to 1,107 in 2018. Thus, the number of firms include in their samples is quite low considering that there were 4,682 listed companies on the Shanghai and Shenzhen Stock Exchanges at the end of 2021.¹ Thus, there have been calls for a comprehensive ESG measure that would enable investors to make informed decisions (Tsang et al., 2023).

Finally, findings based on limited firm-level environmental indicators may not be reliable. For instance, Yang et al. (2024) investigate the impact of environmental disclosure on the cost of debt for Chinese firms. They construct an index based on six categories: waste policies, renewable energy policies, energy-saving policies, environmental certification, environmental recognition, and a final category encompassing other environmental advantages not covered by the preceding five indicators. However, inclusion of items in the sixth category is subject to researchers' personal assessment.

2.3 Environmental Performance and Financial Constraints

Another issue of significance is the channels through which environmental engagements help in improving firm value. Financing constraints, i.e., lack of and/or limited access to finance, pose substantial challenges to firms in improving shareholder wealth. For example, investments are more sensitive to the availability of cash flows for firms that are most likely to experience financing constraints (Fazzari et al., 1988).

Previous research suggests that environment-friendly practices can play a crucial role in alleviating financial constraints by enhancing corporate, financial stability and economic resilience (Boubakri et al., 2021; Galletta et al., 2022). Furthermore, proactive environmental disclosures can reduce information asymmetry with stakeholders, leading to better access to financing (DeLisle et al., 2024; Houston & Shan, 2022).

¹ <https://www.chinabankingnews.com/2022/05/01/chinas-listed-companies-post-over-19-profit-rise-in-2021/>

A firm's environmental commitments can also help overcome implicit financing barriers related to sustainability and facilitate access to long-term financing options (Cao et al., 2023).² Consequently, firms facing financial challenges are increasingly incentivized to improve their environmental commitments and disclosures to gain a competitive advantage in the capital lending market (Huang et al., 2023; Leong & Yang, 2021; Zhou & Gan, 2022).

Overall, the divergence in the ESG scores provided by various rating agencies motivates us to develop a comprehensive environmental commitment index that would enable an objective assessment of firm's sustainability credentials. Further, we also examine the role of financial constraints in the relationship between green commitments and firm value.

3. Data and Methodology

3.1 Data sources

We manually collect firm-level environmental disclosures from their annual and CSR reports, independent environmental reports, and any other publicly available source. We collect data under the six distinct environmental categories, as explained in section 3.2 below. Additionally, we compile data on firms' financial performance, their management profile, and related environmental matters. Firm-level data is obtained from the Chinese Research Data Services Platform (CNRDS) and the China Stock Market & Accounting Research Database (CSMAR).

Our sample includes all A-share listed companies for the period from 2015 to 2021. Our sample starts from 2015 because it marks China's formal commitment to the climate change objectives outlined in the Paris Agreement. Prior to 2015, environmental information disclosures by Chinese firms were either limited in detail or absent. Data about firms' financials is from 2016 to 2022, since we are interested in measuring the impact of environmental commitment on future financial performance. We exclude Special Treatment stocks, Particular Transfer stocks, and stocks belonging to recently

² Green credit provided by 21 large banks in China more than doubled from 4.85 trillion RMB at the end of June 2013 to 10.6 trillion RMB at the end of June 2019.

Source: <http://greenfinance.xinhua08.com/a/20191227/1905011.shtml> (in Chinese)

listed IPOs.³ Additionally, we exclude stocks for which we do not have insufficient data. After the screening process, our final sample comprises 23,315 stock-year observations across 5,054 unique firms. We winsorize data at the 1% and 99% percentiles to mitigate the impact of extreme values.

We include financial firms in our sample for the following two reasons. First, according to the Wind database, the financial sector companies represent over 20% of the total market capitalization of the A share market. Second, many previous studies include financial firms when examining the relationship between firm performance and environmental risk. For example, Bolton & Kacperczyk (2021) investigate the impact of carbon emissions on US stock returns using a sample of 3,421 firms, including 260 banks, 111 insurance companies, and 92 capital market firms. In a subsequent study, Bolton & Kacperczyk (2023) expand their analysis to 14,400 firms across 77 countries, including China. They find a positive association between stock returns and the level and growth rate of carbon emissions across all sectors for most countries. Similarly, Chen et al. (2023) also include financial firms in constructing composite firm-level ESG scores for A-share stocks in China.

3.2 Green Commitment (GC) index

We construct a comprehensive firm-level Green Commitment (GC) index for Chinese firms to avoid the flaws in ESG ratings provided by rating agencies such as Refinitiv, Bloomberg, etc. Our scoring system comprises three key components: the identification of pertinent environmental issues, the evaluation of firm-level indicators, and the aggregation of scores.

We establish an index scoring hierarchy encompassing six distinct environmental categories that have been often studied in isolation in existing research. These include: (I) Presence of Environmental Management System (Hernandez-Vivanco et al., 2019; Wang & Liu, 2023), (II) Pro-Environmental Human Resource Management (Daugaard, 2020; Marrucci et al., 2021; Subramanian et al., 2016), (III) Disclosure of Environmental Spending (Martin & Moser, 2016; Qian et al., 2023), (IV) Disclosure of

³ We exclude these stocks to maintain data comparability and reliability following other studies on China (e.g., see Chen et al., 2023; Wang et al., 2024; Xiao et al., 2023; Yang et al., 2024).

Environmental Protection Performance (Wagner & Schaltegger, 2004; Zhang, 2023), (V) Credibility of Environmental Disclosures (Liao et al., 2023; Wen et al., 2022), and (VI) Effectiveness of Environmental Governance (Chen & Xie, 2022; Tomlinson et al., 2020).

For each of these six categories, we utilize various firm-level indicators to measure its commitment to a specific environmental issue. Specifically, if a firm discloses information or takes pro-environmental actions, we assign it a value of 1 and 0 otherwise. Each indicator contributes to a firm's overall index score. Similar index construction approach has been widely used in past studies. La Porta et al. (1997, 1998) develop an anti-director rights index by aggregating six dummy variables, each representing a different shareholder rights. Gompers et al. (2003) combine 24 binary corporate governance variables into a singular additive index to measure takeover protection and managerial entrenchment. Gu et al. (2018) construct a comprehensive limits-of-arbitrage index by summing up six individual firm-level limits-of-arbitrage indicators. Figure 1 visually illustrates the relationship between these six environmental categories and firm value. A detailed discussion of each category is given in Appendix 1. Details of the data collection procedure and sample data collection codes are provided in Appendix 2 and Appendix 3, respectively.

[Insert Figure 1 About Here]

To mitigate subjective bias, we employ a dummy variable approach for several firm-level indicators to assess firms' environmental commitment across each category. Notably, Berg et al. (2022) observe that discrepancies in ESG ratings are influenced by "weight divergence" that arises from rating agencies assigning different weights to the same attribute. To address this, we use equal weights for all environmental issues, thereby mitigating the "weight" divergence bias. This approach aligns with previous studies, including China-based research (Widyawati, 2020; Zhang, 2023). Finally, we aggregate scores from a total of 20 proxies to derive an overall GC index score, which we standardize using the cross-sectional mean and standard deviation. This process yields a firm's GC index score, which we use as a measure of its environmental commitment. In Table 1, we present a summary of 20 environmental indicators.

[Insert Table 1 About Here]

Our GC index also makes several improvements compared to composite firm-level ESG scoring system proposed by Chen et al. (2023). First, Chen et al. (2023) restrict their environmental rating categories to issues related to environmental risk, such as risk exposure, pollution, and natural resources. These indicators are backward-looking and may suffer from optimism bias (Dhaliwal et al., 2011; Tang et al., 2023). In contrast, our GC index uses forward-looking environmental indicators. Specifically, we include categories related to environmental spending and pro-environmental human resource management, both of which have a potentially lasting impact on firms' environmental commitment.

Second, Chen et al. (2023) ignore the governance role of directors and institutional investors with environmental expertise. Their governance ratings primarily use board independence and institutional shareholdings. However, prior research has demonstrated that managerial decision-making is influenced by their past environmental experience. (Amore et al., 2019; Dokko et al., 2009). To bridge this gap, our GC index explicitly incorporates environmental governance as an important indicator of a firm's environmental commitment.

Finally, Chen et al. (2023) assign varying weights to different environmental issues across economic sectors, potentially introducing a "weight divergence" bias (Berg et al., 2022). For instance, in their index scoring system, environmental risk exposure receives 9.0% (7.0%) topic weight for stocks in the materials (health care) sector, while pollution and emission control receive 10.0% (7.0%) weights, respectively. Such a subjective weighting scheme may cause bias in environmental performance ratings. To avoid the weight bias, we adopt equal-weighted scheme for all environmental categories.

3.3 Measurement of stock return performance

For estimating risk-adjusted returns, we use the Fama & French (1993, 2015) five-factor (FF5) model that includes market (MKT), size (SMB), book-to-market (HML),

investment (CMA), and profitability (RMW) factors. We also extend this to a six-factor (FF6) model, by including Carhart's (1997) momentum (UMD) factor.

$$\mathbf{FF5: } RET_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \varepsilon_{i,t} \quad (1)$$

$$\mathbf{FF6: } RET_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{UMD} UMD_t + \varepsilon_{i,t} \quad (2)$$

where RET denotes the stock returns.

We estimate the cross-sectional relation between GC scores and expected returns using Fama & MacBeth (1973) regressions. We evaluate the average values of the slope coefficients over time to forecast one-month-ahead stock returns both with and without control variables:

$$RET_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} GC_{i,t} + Controls_{i,t} + Ind_{i,t} + \varepsilon_{i,t} \quad (3)$$

where $RET_{i,t+1}$ is the realized returns, $GC_{i,t}$ is the Green Commitment index score of stock i at time t , and Controls denote control variables observable at time t for stock i . We control for industry-specific factors, we include industry (Ind) dummies. ε represents the random error term. Following, prior empirical studies on Chinese stock markets (e.g., see Han & Shi, 2022), we also include: market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book value of assets (AG), the 11-month momentum returns (MOM), the short-term return reversal (REV), idiosyncratic volatility (IVOL), and annual stock turnover ratio (ASTO). The first four control variables are common risk factors used in the Fama-French five-factor model. The variable MOM captures medium-term return momentum, commonly used to explain cross-sectional returns (Asness et al., 2013; Carhart, 1997; Hong et al., 2000; Novy-Marx, 2012). The variable REV corresponds to a contrarian trading, which is considered more appropriate compared to the momentum trading in Chinese stock market (Chen et al., 2022; Yu et al., 2019). The variable IVOL represents firm-specific risk (Ang et al., 2006; Gu et al., 2018, 2019; Gui & Zhu, 2021; Han & Shi, 2022). The variable ASTO is a proxy for investor sentiment (Chen et al., 2014; Cheng & Shi, 2020; Liu et al., 2019). These control variables are similar to the ones used by Chen et al. (2023) for the cross-sectional return analysis. Detailed definitions of these variables are given in Table A.1 in the Appendix 4.

To address potential look-ahead bias, we introduce a six-month lag for environmental information disclosed in financial reports when measuring the association between GC scores and stock returns. For instance, disclosures made in December 2018 reports are used for the GC-based long-short portfolio built in June 2019.

3.4 Measurement of operating performance

We consider two proxies for operating performance, financial returns and operational profitability. Financial returns are measured using the Return on Assets (ROA) ratio, calculated by dividing net profits by the book value of assets. Operational profitability is captured by Operating Profit Margin (OPM) determined by scaling the operating profit with total revenue.

To assess the impact of environmental commitment on value, we construct model 4:

$$OP_{i,t+1} = \alpha_0 + \alpha_1 GC_{i,t} + Controls_{i,t} + Ind_{FE} + Year_{FE} + \varepsilon_{i,t} \quad (4)$$

where $OP_{i,t+1}$ denotes operating performance proxied by either ROA or OPM at time $t+1$, $GC_{i,t}$ is the Green Commitment index score of stock i at time t and Controls are control variables observable at time t for stock i . Details of variables are provided in Table A1. We also control for industry (Ind) and year (Year) fixed effects. ε represents the random error term.

Chen et al. (2023) report a positive correlation between current operating performance and the past performance. We therefore run an autocorrelation test. The Durbin-Watson test statistics are below 1 for both ROA and OPM, indicating strong positive first-order autocorrelation in the operating performance metrics. Hence, we include a lagged term for the Operating Performance (OP) in model 5.

$$OP_{i,t+1} = \alpha_0 + \alpha_1 GC_{i,t} + \alpha_2 OP_{i,t} + Controls_{i,t} + Ind_{FE} + Year_{FE} + \varepsilon_{i,t} \quad (5)$$

where the added explanatory variable $OP_{i,t}$ denotes operating performance at time t . Other independent variables are the same as those in Model 4.

4. Empirical Results

4.1 Summary statistics of variables

Table 2 provides an overview of the descriptive statistics for the GC index and control variables. Panel A presents the time-series averages of the cross-sectional distribution statistics while Panel B provides the correlation matrix between the GC index and the control variables. In Panel A, we observe that the median GC score is -0.049, which is notably lower than the mean value of -0.004. Additionally, the 25th percentile mean is -0.834, indicating a significant deviation from zero, while the 75th percentile mean is 0.552. These statistics suggest that the distribution of GC index scores is left-skewed, with a higher concentration of low scores compared to high scores. The average raw GC score across the sample is 3.043, indicating that firms, on average, achieve a score of approximately 3 out of a possible 20 items. The descriptive statistics for the control variables are similar to those reported in previous studies (e.g., see Chen et al., 2023; Wang et al., 2024).

[Insert Table 2 About Here]

In Panel B, correlations between the GC index and control variables are positive except for IVOL and ASTO. Specifically, the Spearman correlation coefficient between GC and SIZE is 0.273, suggesting a positive correlation between large-cap stocks and environmental performance. Conversely, the correlation between IVOL and GC is -0.054, implying that higher GC score firms experience less firm-specific risk. For the remaining variables, the Spearman correlation with GC ranges from 0.025 to 0.069. Results from Pearson correlations are like those from Spearman correlations.

4.2 Risk-adjusted returns of GC portfolios

In this section, we examine whether stocks with high GC scores outperform those with low GC scores. Table 3 presents the risk-adjusted returns of GC terciles based on the Fama-French five- and six-factor models. For each month t in the sample, we categorize stocks into terciles by ascending GC scores, using weights of 30/40/30, from the lowest (Q1) to the highest (Q3) GC portfolio. In month $t+1$, we calculate the value-weighted and equally weighted average returns. Panels A and B report alphas for value-weighted and equal-weighted portfolios, respectively.

[Insert Table 3 About Here]

The results show a significant outperformance by tercile 3 compared to tercile 1 across various specifications. For instance, the alpha of the long-short value-weighted portfolio (Q3 - Q1) is 0.449%, with a t-statistic of 2.878 based on the FF6 model. This confirms that stocks earn a positive and significant GC premium. The monthly alpha of 0.449% equates to an annualized premium of 5.39%, which is economically significant. The findings imply that investors earn positive excess returns by investing in portfolio of stocks with high GC scores and shorting portfolio of stocks with low GC scores.

4.3 Stock-level cross-sectional regressions

To ensure the robustness of the GC premium, we analyze the cross-sectional association between GC scores and expected returns at the individual stock level using Fama & MacBeth (1973) regressions. Table 4 presents the time-series averages of the slope coefficients, along with the Newey-West adjusted t-statistics in parentheses. The univariate regression results in Column 1 reveal a positive and statistically significant relationship between GC scores and the cross-section of future stock returns. Specifically, the average slope for GC is 0.002, with a t-statistic of 2.276, which is significant at the 5% level. The findings suggest that high GC score stocks earn superior returns.

[Insert Table 4 About Here]

In Column 2, we control for stock-specific variables, i.e., market beta, size, book-to-market, asset growth rate, momentum, short-term reversal, idiosyncratic volatility, and turnover. The average slope of GC remains positive at 0.002 and statistically significant.

In Columns 3 and 4, we control for the industry fixed effects. Each month, we categorize stocks into one of the first-level CSI industry classifications and replicate firm-level cross-sectional regressions. As seen from Columns 3 and 4, the average slope coefficients for GC remain significantly positive, with similar magnitudes to ones reported in Columns 1 and 2. Overall, our findings show a positive association between GC scores and future stock returns in China.

4.4 Risk characteristics of GC-sorted portfolios

Our findings of a significant and positive GC premium in China, contrasts those reported which a negative ESG premium in other countries (e.g., Blitz & Fabozzi, 2017; Fabozzi et al., 2008; Hong & Kacperczyk, 2009). Some researchers propose that stocks with high ESG rating scores could be riskier, as they carry a positive correlation with portfolio volatility and underperform during economic recessions (e.g., Ng & Rezaee, 2020; Richey, 2020; Wan et al., 2024). Lakonishok et al. (1994) put forth the idea that abnormal returns associated with higher portfolio volatility or generated during economic downturns might serve as compensation to investors for bearing elevated risks. This motivates us to explore risk characteristics of GC-sorted portfolios to assess whether the risk compensation argument holds.

If GC premium is indeed associated with higher portfolio volatility, we would expect higher risk for portfolios of stocks with high GC scores. To investigate this, we compute standard risk measures, including market betas and standard deviations for both value-weighted and equal-weighted daily tercile portfolios in Panel A of Table 5.,

[Insert Table 5 About Here]

Our findings indicate that stocks with high GC scores exhibit low market betas and standard deviations. The difference in risk between Q3 and Q1 is statistically significant at the 1% level, except in case of equally weighted portfolio where the standard deviations is higher. These results suggest that stocks with high GC scores are less volatile and carry lower systematic risks.

We also explore the time-varying nature of the GC premium to assess whether GC scores reflect fundamental risks. If the abnormal returns associated with high GC stocks are indeed linked to greater fundamental risks, we would expect the high GC portfolios to underperform the low GC portfolios during the bear markets when the marginal utility of consumption is high (Bali et al., 2017; Lakonishok et al., 1994).

We divide the total sample into bull and bear market periods by calculating the average monthly returns. A month is categorized as a ‘bear market’ when the return is lower than the median return, and as a ‘bull market’ otherwise. We then analyze the performance of the GC-sorted tercile portfolios and the GC hedge portfolio that is long on high GC tercile (Q3) and short on low GC tercile (Q1).

Results in Panel B of Table 5 show that, in bull markets, the average value-weighted return to the hedge portfolio is -0.271%, which is insignificant. In contrast, in bear markets, the hedge portfolio’s value-weighted return is 0.612%, which is significant at the 10% level. Therefore, investing in firms with high environment commitment does not seem to expose investors to greater downside risk. Overall, we find no evidence to support the risk compensation argument.

4.5 GC scores and future operating performance

The positive GC premium suggests that investors may underreact to good news about a firm as indicated by its high GC score. To explore this further, we examine whether firms with high GC scores demonstrate superior operating performance in the subsequent year.

Table 6 presents the impact of GC scores on future operating performance. The results based on Model 4 are shown in Columns 1 and 3, while Columns 2 and 4 display results for Model 5, which includes lagged values for ROA and OPM. Across both models, the coefficients for GC are consistently positive and statistically significant at the 1% level. These findings indicate that firms with high GC scores experience significant improvements in their future operational performance.

[Insert Table 6 About Here]

4.6 Financial constraints and relationship between environmental commitment and operating performance

In this section, we employ a model proposed by Baron & Kenny (1986) to investigate whether the high environmental commitment facilitates mitigation of financial constraints which in turn improves a firm’s operating performance.

We consider two distinct proxies for financial constraints: the KZ index (Kaplan & Zingales, 1997) and the WW index (Whited & Wu, 2006).⁴ The KZ index is a linear combination of the following variables with signs in parentheses: cash flow to capital (−), Tobin’s Q (+), debt to total capital (+), dividends to capital (−), and cash holdings to capital (−). On the other hand, the WW index is a linear combination of cash flow to total assets (−), dividend policy indicator (−), long-term debt to total assets (+), log of total assets (−), sales growth (−), and the firm’s industry sales growth (+). A higher value of either the KZ or the WW index would indicate a greater level of financial constraints. The KZ and WW have been extensively used as proxies for financial constraints in previous studies, including those based in China (Ahamed et al., 2023; Guariglia & Yang, 2016; Li, 2011). We use Model 6 to test whether green commitment can reduce financial constraints:

$$FC_{i,t+1} = \beta_0 + \beta_1 GC_{i,t} + Controls_{i,t} + Ind_{FE} + Year_{FE} + \varepsilon_{i,t} \quad (6)$$

where FC indicates financial constraint variables are KZ and WW, GC is the Green Commitment index, Controls are the control variables listed in Table A1, Ind (Year) indicates industry (year) fixed effects, and ε represents the random error term.

To investigate the mediating role of financial constraints in the relationship between GC and operating performance, we use Model 7:

$$OP_{i,t+1} = \gamma_0 + \gamma_1 GC_{i,t} + \gamma_2 FC_{i,t} + Controls_{i,t} + Ind_{FE} + Year_{FE} + \varepsilon_{i,t} \quad (7)$$

where OP denotes operating performance proxied by either ROA or OPM, GC is the Green Commitment score, FC indicates financial constraint represented by either KZ or WW, Controls are the control variables listed in Table A1, and ε is the error term.

Table 7 displays the results for Models 4, 6, and 7. The results of the Model 4 in Column 1 serve as the baseline to compare results obtained by using Models 6 and 7. Panels A and B show results where the next-year operating performance is measured by ROA

⁴ Whited & Wu (2006) report an approximate zero correlation between the KZ and WW indices. Hence we use both to ensure the robustness of our findings. Hadlock & Pierce (2010) introduce the SA index, derived from the size and age of a firm. However, we do not use the SA index because the firm’s age, one of the two components of the SA index, is unaffected by the firm’s environmental practices.

and OPM, respectively. Columns 1 – 3 report results using the KZ index, while Columns 4 – 6 present results with the WW index.

[Insert Table 7 About Here]

In Panel A, Column 2, the GC coefficient is -0.067 with a t-statistic of -2.656, which suggests that greater GC reduces financial constraints. In Column 3, the GC and KZ coefficients are 0.003 and -0.021 respectively, with corresponding t-statistics of 5.383 and -53.098. Notably, the GC coefficient of 0.003 in Column 3 is less than the GC coefficient of 0.005 in Column 1, indicating that the introduction of the financial constraint variable diminishes the positive effect of GC scores on ROA. This pattern persists when we substitute the KZ index with the WW index in Columns 4 to 6. Panel B's results echo those in Panel A. Overall, the results suggest that greater environmental commitments reduce financial constraints and improve a firm's operating performance.

4.7 Industry competition, ownership structure and financial constraints

Drawing on the literature that examines the impact of the level of competition (e.g., Bernini & Montagnoli, 2017) and ownership structure (e.g., Liu et al., 2012; Poncet et al., 2010) on financial constraints faced by firms, we undertake further analysis.

4.7.1 Industry competition

First, we use industry competition. Bernini & Montagnoli (2017) suggest that less developed legal systems can increase competitive pressure for both the demand and supply of credit. Specifically, while demand for credit is elevated in competitive industries, many firms are discouraged from applying for loans due to high collateral requirements and credit costs. Given that China remains a transition economy (Cubizol, 2018), it is expected that firms operating in highly competitive industries will face greater financial constraints. This may affect the positive relation between GC score and operating performance.

Following Do et al. (2022), we calculate the Herfindahl-Hirschman Index (HHI) based on a firm's market share within its primary industry category to measure the extent of competition. We use the first level of the CSI industry classification. Firms belonging

to industries in the top 50% of HHI index values are categorized as those facing low market competition, and the remaining as those facing high competition. We conduct the baseline regression for subsamples of firms and present the results in Table 8. Panels A and B display the results for ROA and OPM, while Columns 1 and 2 show the results for low and high market competition, respectively.

[Insert Table 8 About Here]

For the low market competition firms, Panel A shows the GC coefficient of 0.003 with a t-statistic of 1.007. On the other hand, for the high market competition firms, the GC coefficient is 0.006 with a t-statistic of 6.665. Panel B exhibits similar results when the performance is measured with OPM. These findings suggest that GC has a positive impact on operational performance when there is high competition.

4.7.2 Ownership structure

The second proxy for heterogeneity analysis is ownership structure. In China, State-Owned Enterprises (SOEs) often receive preferential treatment from banks due to their government affiliation and therefore face fewer financial constraints compared to non-SOEs (Liu et al., 2012; Poncet et al., 2010). Additionally, in SOEs production and operational decisions are often directed by government policies rather than market forces. Empirical evidence suggests that SOEs in China exhibit lower financial performance and higher surplus employment (Wang & Shailer, 2022). Given these factors, we propose that the positive effects of environmental commitment on operational performance may be less pronounced in SOEs due to their relatively privileged position.

Following Allen et al., (2022), we identify SOEs as firms where the state holds more than 50% equity, and rest as non-SOE firms. We then re-run the baseline models. Results presented in Columns 3 and 4 of Table 8. Panel A, which examines ROA, shows that the GC coefficient for SOEs is 0.001 with a t-statistic of 0.603. In contrast, the GC coefficient for non-SOEs is 0.007 with a t-statistic of 7.169. Panel B displays a similar pattern with OPM; the GC coefficient remains insignificant for SOEs, but it is significant at the 1% level for non-SOEs. These results suggest that the positive impact

of GC on operating performance is significant only for non-SOEs who are likely to face greater financial constraints than SOEs.

5. Robustness Checks

5.1 Endogeneity issue

Our baseline results reported so far could be influenced by endogeneity. In our research, endogeneity could arise from three potential sources. The first could be the omitted variable bias as we may fail to include some potentially correlated variables in Model 4. Second, the endogeneity may arise from the errors in the variable measurement (Roberts & Whited, 2013). Finally, our results could be affected by the reverse causality between environmental commitment and operating performance (Chen & Xie, 2022). To-performing companies may have more resources to spend on environmental initiatives thereby attaining higher GC scores. To ensure the robustness of our results, we employ the Propensity Score Matching (PSM) and the Two-Stage Least Squares (2SLS) regression.⁵

5.1.1 Propensity score matching

To robustly assess the impact of GC on a company's operational performance, we follow the approach of He et al. (2024) to compare two groups of firms: those in the top 30% of GC scores (treatment group) and those in the bottom 30% (control group). We employ the nearest neighbor matching algorithm with a 0.05 caliper value in the matching process. We find that our matching process is valid since the differences in the matching variables between the two groups are not significant (results not reported here but are available on request).

We include control variables i.e., market beta, company size, BM ratio, asset growth rate, and momentum which are considered as common risk factors (Fama & French, 2015). The regression results for the matched samples are reported in Table 9, where Column 1 (2) uses next-year ROA (OPM) as the dependent variable. We find that the

⁵ The Heckman's selection model (Heckman, 1979) is also used to address the omitted variable bias, and we find no evidence of selection bias. We do not discuss or report the results for brevity, but they are available on request.

coefficient for GC is statistically significant (t-statistic of 7.220 (7.619) in Column 1 (2)) and confirms that our baseline results are robust.

[Insert Table 9 About Here]

5.1.2 Two-stage least-squares regression

To address the reverse causality,⁶ we use the Two-Stage Least-Squares (2SLS) Instrumental Variable (IV) approach (Wooldridge, 2013, chapter 15). The most formidable task in 2SLS is identifying appropriate instruments that need to satisfy both relevance and exogeneity conditions.

We use the industry-province average GC score (GC_IV) as the IV which is expected to influence the firm-level GC scores (relevance condition) but is unlikely to have a direct effect on future operating performance of the firm (exogenous condition). Several previous studies use this approach. El Ghouli et al. (2011) utilize the industry average CSR score as IV while examining the impact of CSR on the cost of equity for a large sample of US firms. Similarly, Breuer et al. (2018) too use the country-industry average CSR scores as IV to examine the impact of CSR on the cost of equity based on a large global sample. In the Chinese context, Wang et al. (2024) use the industry average ESG rating disagreement as IV in their work looking at effect of ESG rating disagreement on stock returns.

The results of 2SLS regressions are reported in in Table 10. Column 1 presents the results of the first stage, which regresses GC scores on the IV (GC_IV) and control variables. The coefficient of GC_IV is 0.857 is highly significant at the 1% level. Columns 2 and 3 present the results of the second stage regressions for next-year ROA and OPM, respectively. The coefficient of GC scores for predicting next-year ROA (OPM) is 0.007 (0.036) and statistically significant with a t-value of 3.569 (4.346) in column 2 (3). Overall, the 2SLS confirm that our baseline results which show greater environmental commitments improve operating performance are robust.

⁶ We run a Granger causality diagnostic test for the reverse causality and reject the null hypothesis that lagged operating performance does not Granger-cause GC scores. Thus, there is a possibility for reverse causality, which requires further analysis. We would like to thank the anonymous reviewer for suggesting this test.

[Insert Table 10 About Here]

5.2 Alternative proxies for operating performance

So far, we have used ROA and OPM as proxies for operating performance. However, previous studies have used Return on Equity (ROE) and Net Profit Margin (NPM) as measures of operating performance (e.g., see Zhang & Rezaee, 2009). To further check that our findings are robust, we re-run our baseline regression with ROE and NPM. The results remain unchanged and confirm that regardless of the measures of operating performance used, the impact of GC score on operating performance remain positive and statistically significant. We do not report these results for brevity, but they are available on request.

5.3 Alternative instrumental variable for 2SLS

In the 2SLS analysis, we used industry-province average of GC scores as IV. However, Guo et al. (2024) argue that industry average is not a good exogenous variable, and they recommend using ESG investments instead. They contend that institutional investors who prefer green assets influence firms through active engagement and continuous monitoring. Hence, we conduct further analysis by using the number of Green Institutional Investors at firm level (GI_IV) as an alternative IV. Results based on 2SLS analysis are qualitatively similar and confirm our previous findings that high GC firms show improved operating performance. These results are not reported for brevity, but they are available on request.

5.4 Inclusion of financial firms

Due to significant differences in operating characteristics, environmental performance, and environmental disclosures between financial and non-financial firms, our study may encounter potential bias since our sample includes financial firms. Although we address this issue by using industry-adjusted measures in our index construction, this adjustment may not be entirely sufficient.⁷

⁷ We would like to thank the anonymous reviewer for this important observation.

To address this concern, we further test the robustness of our results by excluding financial stocks from our sample and re-running the analysis. Table 11 presents the findings of portfolio analysis, showing that the alphas of GC-sorted portfolios without financial stocks remain positive and statistically significant. For example, the alpha of the long-short value-weighted portfolio (Q3 - Q1) is 0.498%, with a t-statistic of 2.870 based on the FF6 model. The findings confirm significant outperformance of tercile 3 compared to tercile 1 across various specifications. The magnitude and significance of alpha in Table 11 are comparable to those reported in Table 3.

[Insert Table 11 About Here]

In Table 12, we further analyze the operating performance of the sample comprising only non-financial stocks. The results demonstrate that non-financial firms with higher GC scores experience significant improvement in next-year's operating performance. The above findings confirm that our baseline results are unaffected by the inclusion of financial stocks.

[Insert Table 12 About Here]

6. Conclusions

ESG investing has gained significant popularity in recent years due to the growing environmental concerns. However, existing literature presents mixed empirical evidence regarding the impact of environmental investing on firm performance. In this study, we introduce a comprehensive GC index to assess firm-level environmental commitment among Chinese listed companies during the period from 2015 to 2021. Our GC index includes various previously unexplored environmental dimensions, such as environmental management and governance. By using dummy variables and an equal-weighting scheme, our GC index mitigates the subjective bias reported in ESG ratings.

Our analysis reveals that firms with high GC scores show superior stock returns. This is confirmed by both portfolio analysis and cross-sectional regressions. We also find a positive relationship between GC scores and future operating performance. The

findings highlight that environmental investing can enhance shareholder value. Our results remain robust after addressing various limitations and endogeneity concerns.

Additionally, we show that greater environmental commitments can improve future operating performance by alleviating financial constraints. The positive impact is particularly significant for those firms that operate in highly competitive industries and the ones that are not state owned.

The findings reported in the study have important policy and research implications. Managers and board of directors could enhance shareholder value through greater environmental commitments. Policymakers could incentivize firms to increase their environmental commitments, to expedite progress towards achieving a low-carbon economy. Additionally, our GC index can be adapted for use in other countries, potentially helping to reconcile the diverse empirical findings regarding the impact of environmental investing on firm value.

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Table 1 Scoring of Green Commitment (GC) Index

No.	Scoring Items (Dummy variables, Y = 1, N = 0)	Related Studies
(I) Presence of environmental management system		
1	Disclosure of establishing system regarding environmental risk and performance	(Hernandez-Vivanco et al., 2019; Wang & Liu, 2023)
2	Disclosure of implementing ISO14001	(Wang & Liu, 2023; Zhang, 2023)
3	Disclosure of implementing ISO9001	(Wang & Liu, 2023; Zhang, 2023)
(II) Pro-environmental human resource management		
4	Disclosure of environment performance-based management system	(Marrucci et al., 2021; Subramanian et al., 2016)
5	Disclosure of employee training in environmental management and operation	(Subramanian et al., 2016; Zhang, 2023)
6	Disclosure of employee participation in specific environment projects	(Marrucci et al., 2021; Subramanian et al., 2016)
(III) Disclosure of environmental spending		
7	Disclosure of expenditures on environmental investment (e.g., R&D, technologies)	(Martin & Moser, 2016; Qian et al., 2023)
8	Disclosure of expenditures on environmental improvement (e.g., pollution restoration, environmental rehabilitation)	(Martin & Moser, 2016; Qian et al., 2023)
9	Disclosure of environment innovations (e.g. patents and/or innovations to enhance environmental performance)	(Hao et al., 2022; Xu et al., 2021)
(IV) Disclosure of environmental protection performance		
10	Under-emission of carbon dioxide after controlling for total output, industry and year	(Bolton & Kacperczyk, 2021; Han et al., 2023)
11	Disclosure of pollutant reduction	(Yang et al., 2024; Zhang, 2023)
12	Disclosure of energy saving	(Yang et al., 2024; Zhang, 2023)
(V) Credibility of environmental disclosures		
13	Disclosure of adopting GRI sustainability reporting guidelines	(Wen et al., 2022; Yang et al., 2021)
14	Disclosure of certification regarding environmental performance by independent agency	(Kimbrough et al., 2024; Simnett et al., 2009)
15	Disclosure of auditors from the Big 4 firms (i.e., PwC, Deloitte, EY, and KPMG)	(Kimbrough et al., 2024; Simnett et al., 2009)
16	Disclosure of internal system deficiency	(Ashbaugh-Skaife et al., 2009; Ji et al., 2017)
(VI) Effectiveness of environmental governance		
17	The presence of executive directors with education degree or work experience in environmental areas	(Cosma et al., 2021; Tomlinson et al., 2020)
18	The presence of independent directors with education degree or work experience in environmental areas	(Cosma et al., 2021; Tomlinson et al., 2020)
19	The presence of senior managers with education degree or work experience in environmental areas	(Amore et al., 2019; Dokko et al., 2009)
20	The presence of institutional investors whose investment objective statements include environment-related key words	(Chen & Xie, 2022; Liu et al., 2023)

Table 2 Descriptive statistics

This table presents summary statistics for the GC index and key variables used in the cross-sectional regressions. Panel A reports the sample descriptive statistics. Panel B reports the time-series average of the Pearson (above diagonal) and Spearman (below diagonal) cross-sectional correlations. The sample period spans from 2015 to 2021.

Panel A: Descriptive statistics										
Variable	Mean	Std	Min	P25	Median	P75	Max			
GC	-0.004	0.988	-1.257	-0.834	-0.049	0.552	2.910			
Raw GC	3.043	0.103	2.899	2.964	3.028	3.142	3.173			
BETA	1.116	0.444	-0.387	0.887	1.135	1.364	2.506			
SIZE	22.929	1.229	20.938	22.068	22.700	23.547	27.362			
BM	0.323	0.153	0.006	0.216	0.311	0.422	0.737			
AG	0.186	0.428	-0.377	0.005	0.090	0.227	2.912			
MOM	0.261	0.766	-0.497	-0.131	0.046	0.335	4.166			
REV	0.005	0.122	-0.211	-0.059	-0.015	0.041	0.654			
IVOL	0.097	0.049	0.032	0.061	0.086	0.120	0.282			
ASTO	1.784	1.198	0.118	0.928	1.488	2.335	6.053			
Panel B: Correlation matrix										
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
GC	(1)		0.037	0.340	0.051	0.008	0.019	0.008	-0.070	-0.111
BETA	(2)	0.034		-0.107	0.018	0.040	0.146	-0.111	0.014	0.323
SIZE	(3)	0.273	-0.118		-0.205	0.067	-0.075	0.002	-0.135	-0.328
BM	(4)	0.057	0.007	-0.208		0.039	-0.079	-0.052	-0.191	-0.123
AG	(5)	0.058	0.066	0.126	0.003		0.232	0.011	0.023	-0.028
MOM	(6)	0.069	0.031	0.022	-0.102	0.241		-0.043	0.248	0.256
REV	(7)	0.025	-0.100	0.051	-0.063	0.012	-0.010		0.400	-0.020
IVOL	(8)	-0.054	0.069	-0.115	-0.220	0.023	0.267	0.240		0.276
ASTO	(9)	-0.108	0.458	-0.362	-0.097	-0.057	0.153	-0.071	0.264	

Table 3 Alphas of portfolios sorted by GC scores

At the end of each month, we sort stocks into quintiles in ascending order of GC index values, where tercile 1 (3) consists of stocks with the lowest (highest) GC scores. We also form a long-short portfolio (Q3-Q1) by being long on tercile 3 and short on tercile 1. In Panel A (B), we report the alphas (in percentage) relative to factor models (FF5 and FF6) based on average next-month value-weighted (equal-weighted) returns to quintile and long-short portfolios. FF5 is the alpha relative to market, size, book-to-market, investment, and profitability factors. FF6 is the alpha relative to market, size, book-to-market, investment, profitability, and momentum factors. Newey-West adjusted t-statistics are given in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Model	Q1 (Low)		Q2 (Med)		Q3 (High)		(Q3-Q1)	
Panel A: Alphas based on value-weighted returns								
FF5	-0.579***	(-4.363)	-0.332**	(-2.408)	0.051	(1.102)	0.461***	(2.946)
FF6	-0.556***	(-4.328)	-0.322**	(-2.347)	0.063	(1.372)	0.449***	(2.878)
Panel B: Alphas based on equal-weighted returns								
FF5	-0.374***	(-3.757)	-0.117	(-1.523)	0.107	(1.313)	0.311**	(2.177)
FF6	-0.353***	(-3.652)	-0.104	(-1.322)	0.112	(1.368)	0.295**	(2.143)

Table 4 Fama-Macbeth cross-sectional regressions

This table reports time-series averages of the slope coefficients obtained from regressing next-month returns on GC and a set of lagged predictive variables using Fama-MacBeth methodology. The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic volatility (IVOL), and annual stock turnover (ASTO). Columns (1) and (2) present univariate and multivariate regression results, respectively. Columns (3) and (4) present the same set of regression results, controlling for the industry effect. Newey-West adjusted t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1) Ret _{t+1}	(2) Ret _{t+1}	(3) Ret _{t+1}	(4) Ret _{t+1}
GC _t	0.002** (2.276)	0.002*** (3.300)	0.002* (1.786)	0.001*** (3.224)
BETA _t		0.006 (1.230)		0.007 (1.403)
SIZE _t		-0.003* (-1.903)		-0.003 (-1.602)
BM _t		0.000 (0.004)		0.002 (0.475)
AG _t		0.000 (0.261)		0.000 (0.283)
MOM _t		0.013*** (3.017)		0.012*** (2.982)
REV _t		-0.009 (-0.734)		-0.010 (-0.924)
IVOL _t		-0.141*** (-6.707)		-0.134*** (-6.476)
ASTO _t		-0.005*** (-5.505)		-0.005*** (-5.968)
Intercept	0.003 (0.401)	0.060** (2.344)	-0.010 (-0.896)	0.048** (2.316)
Observations	255,037	255,037	255,037	255,037
Adj R ²	0.006	0.094	0.041	0.114
Industry effect	N	N	Y	Y

Table 5 Risk characteristics of GC-sorted portfolios

At the end of each month, we sort stocks into quintiles in ascending order of the GC index values, where tercile 1 (3) consists of stocks with the lowest (highest) GC scores. We also form a long-short portfolio (Q3-Q1) by being long on tercile 3 and short on tercile 1. Panel A reports market beta, and standard deviation for each portfolio. We split the whole sample periods into bull and bear markets based on monthly market returns. We classify a month as ‘bear markets’ month when the month’s monthly market return is lower than the sample median of monthly returns, and as ‘bull markets’ month otherwise. Panel B reports both value- and equal-weighted returns for GC-sorted portfolios and the hedge portfolios in both bull and bear markets. Returns are given in percentage terms. T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	Q1 (Low)	Q2 (Med)	Q3 (High)	(Q3-Q1)	
Panel A: Portfolio-level risks					
Value-weighted returns					
Market beta	1.176	1.145	0.912	-0.263***	(-13.696)
Standard deviation	0.054	0.051	0.041	-0.013***	(-4.428)
Equal-weighted returns					
Market beta	1.039	1.018	0.952	-0.087***	(-15.059)
Standard deviation	0.057	0.056	0.052	-0.005	(-1.451)
Panel B: Exposure to market risks					
Value-weighted returns					
Bull markets	4.830	4.753	4.559	-0.271	(-0.531)
Bear markets	-2.359	-2.212	-1.748	0.612*	(1.922)
Equal-weighted returns					
Bull markets	3.429	3.700	3.881	0.452**	(2.182)
Bear markets	-3.113	-2.997	-2.819	0.294	(1.317)

Table 6 GC scores and future operating performance

This table reports results from regressing next-year operating performance on GC and a set of lagged predictive variables using industry-year fixed effect models. The dependent variable is Return on Assets (ROA) and Operating Profit Margin (OPM). The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic risk (IVOL), and annual stock turnover (ASTO). Columns (1) and (2) report the results where the dependent variable is ROA and Columns (3) and (4) report the results where the dependent variable is OPM. In Columns (2) and (4), we also add one-year lag of the firm's own ROA or OPM as control variables. T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1) ROA _{t+1}	(2) ROA _{t+1}	(3) OPM _{t+1}	(4) OPM _{t+1}
GC _t	0.006*** (6.774)	0.005*** (7.400)	0.025*** (7.720)	0.020*** (8.139)
ROA _t		0.394*** (28.627)		
OPM _t				0.423*** (18.346)
BETA _t	0.028*** (13.330)	0.020*** (10.478)	0.087*** (10.526)	0.056*** (7.923)
SIZE _t	0.003*** (3.401)	0.000 (0.426)	0.009*** (2.918)	-0.000 (-0.024)
BM _t	0.011* (1.840)	-0.018*** (-3.999)	0.112*** (4.445)	-0.017 (-0.890)
AG _t	0.014*** (10.129)	0.004*** (3.287)	0.053*** (9.949)	0.014*** (3.111)
MOM _t	0.029*** (24.755)	0.016*** (16.816)	0.084*** (19.125)	0.048*** (13.555)
REV _t	0.073*** (12.006)	0.038*** (6.795)	0.234*** (9.121)	0.116*** (5.552)
IVOL _t	-0.144*** (-9.075)	-0.064*** (-4.447)	-0.518*** (-8.260)	-0.234*** (-4.346)
ASTO _t	-0.009*** (-13.666)	-0.006*** (-11.105)	-0.024*** (-9.687)	-0.015*** (-7.657)
Intercept	-0.049*** (-2.617)	0.004 (0.273)	-0.236*** (-2.952)	-0.000 (-0.001)
Observations	23,315	23,315	23,315	23,315
Adj R ²	0.096	0.212	0.092	0.218
Industry F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y

Table 7 Financial constraints, GC scores and operating performance

This table reports results of mediation analysis, where GC affects operating performance through financial constraints. Panels A and B present results for next-year Return on Assets (ROA) and Operating Profit Margin (OPM), respectively. Columns 1, 2, and 3 report results for models 4, 6, and 7. Columns 4, 5, and 6 report results for models 4, 6, and 7. The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic risk (IVOL), and annual stock turnover (ASTO). T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Operating performance measured by ROA _{t+1}						
	ROA _{t+1}	KZ _{t+1}	ROA _{t+1}	ROA _{t+1}	WW _{t+1}	ROA _{t+1}
GC _t	0.005*** (5.614)	-0.067*** (-2.656)	0.003*** (5.383)	0.005*** (5.614)	-0.003*** (-5.591)	0.004*** (4.819)
KZ _{t+1}			-0.021*** (-53.098)			
WW _{t+1}						-0.252*** (-5.487)
Controls	Y	Y	Y	Y	Y	Y
Observations	21,240	21,240	21,240	21,240	21,240	21,240
Adj R ²	0.095	0.225	0.329	0.095	0.392	0.144
Industry F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Panel B: Operating performance measured by OPM _{t+1}						
	OPM _{t+1}	KZ _{t+1}	OPM _{t+1}	OPM _{t+1}	WW _{t+1}	OPM _{t+1}
GC _t	0.018*** (6.115)	-0.067*** (-2.656)	0.014*** (5.599)	0.018*** (6.115)	-0.003*** (-5.591)	0.016*** (5.437)
KZ _{t+1}			-0.055*** (-36.217)			
WW _{t+1}						-0.732*** (-5.315)
Controls	Y	Y	Y	Y	Y	Y
Observations	21,240	21,240	21,240	21,240	21,240	21,240
Adj R ²	0.074	0.225	0.211	0.074	0.392	0.108
Industry F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y

Table 8 The impacts of market competition and ownership structure

This table reports the impacts of market competition and ownership structure on the relationship between GC scores and firm operating performance. Column 1 (2) reports results for subsample firms whose industry's HHI index value is higher (lower) than the cross-sectional median. Column 3 (4) reports results for state-owned enterprises (non-state-owned enterprises). The dependent variables are Return on Assets (ROA) and Operating Profit Margin (OPM). The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic volatility (IVOL), and annual stock turnover (ASTO). T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1) Low Market Competition	(2) High Market Competition	(3) State-Owned Enterprises	(4) Non-State-Owned Enterprises
Panel A: Dependent variable = ROA_{t+1}				
GC _t	0.003 (1.007)	0.006*** (6.665)	0.001 (0.603)	0.007*** (7.169)
Controls	Y	Y	Y	Y
Observations	2,128	21,187	4,810	18,504
Adj R ²	0.109	0.095	0.086	0.104
Industry F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Panel B: Dependent variable = OPM_{t+1}				
GC _t	0.013 (1.304)	0.026*** (7.680)	0.003 (0.663)	0.033*** (8.318)
Controls	Y	Y	Y	Y
Observations	2,128	21,187	4,810	18,504
Adj R ²	0.136	0.086	0.209	0.085
Industry F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y

Table 9 Propensity score matching method

This table reports propensity score matching method results for predicting next-year fundamental performance. Dependent variables in Column (1) and (2) are next-year Return on Assets (ROA) and next-year Operating Profit Margin (OPM), respectively. The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic risk (IVOL), and annual stock turnover (ASTO). T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1) ROA _{t+1}	(2) OPM _{t+1}
GC _t	0.007*** (7.220)	0.028*** (7.619)
BETA _t	0.033*** (13.059)	0.111*** (11.028)
SIZE _t	0.003*** (3.480)	0.013*** (3.491)
BM _t	0.042*** (5.750)	0.252*** (7.707)
AG _t	0.016*** (9.461)	0.062*** (9.705)
MOM _t	0.032*** (23.118)	0.100*** (17.319)
REV _t	0.080*** (10.599)	0.284*** (8.699)
IVOL _t	-0.155*** (-8.757)	-0.627*** (-8.316)
ASTO _t	-0.009*** (-11.995)	-0.025*** (-7.947)
Intercept	-0.074*** (-3.620)	-0.393*** (-4.317)
Observations	19,637	19,634
Adj R ²	0.110	0.110
Industry F.E.	Y	Y
Year F.E.	Y	Y

Table 10 Two-Stage Least Squares (2SLS) method

This table reports 2SLS method results for predicting next-year operating performance. Column 1 presents the first stage regression results, where the dependent variable is GC index score. Columns 2 and 3 present the second stage regression results for next-year Return on Assets (ROA) and Operating Profit Margin (OPM), respectively. The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic risk (IVOL), and annual stock turnover (ASTO). T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, 10%, respectively.

	(1) GC _t	(2) ROA _{t+1}	(3) OPM _{t+1}
GC_IV	0.857*** (54.019)		
GC _t		0.007*** (3.569)	0.036*** (4.346)
BETA _t	0.138*** (7.804)	0.029*** (13.103)	0.085*** (9.947)
SIZE _t	0.282*** (28.616)	0.002** (2.096)	0.004 (1.030)
BM _t	0.452*** (7.694)	0.009 (1.512)	0.101*** (3.908)
AG _t	-0.068*** (-6.324)	0.015*** (9.591)	0.055*** (9.308)
MOM _t	0.022** (2.390)	0.029*** (23.965)	0.083*** (18.558)
REV _t	0.043 (0.816)	0.074*** (11.931)	0.232*** (9.074)
IVOL _t	-0.087 (-0.678)	-0.145*** (-8.887)	-0.520*** (-8.207)
ASTO _t	-0.022*** (-3.343)	-0.009*** (-13.736)	-0.024*** (-9.583)
Observations	22,182	22,182	22,182
Adj R ²	0.451	0.074	0.053
Industry F.E.	Y	Y	Y
Year F.E.	Y	Y	Y

Table 11 Alphas of portfolios sorted by GC scores for non-financial stocks

We conduct robustness check for the analysis in Table 3 by excluding financial stocks from the sample. Then, at the end of each month, we sort stocks into quintiles in ascending order of GC index values, where tercile 1 (3) consists of stocks with the lowest (highest) GC scores. We also form a long-short portfolio (Q3-Q1) by being long on tercile 3 and short on tercile 1. In Panel A (B), we report the alphas (in percentage) relative to factor models (FF5 and FF6) based on average next-month value-weighted (equal-weighted) returns to quintile and long-short portfolios. FF5 is the alpha relative to market, size, book-to-market, investment, and profitability factors. FF6 is the alpha relative to market, size, book-to-market, investment, profitability, and momentum factors. Newey-West adjusted t-statistics are given in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

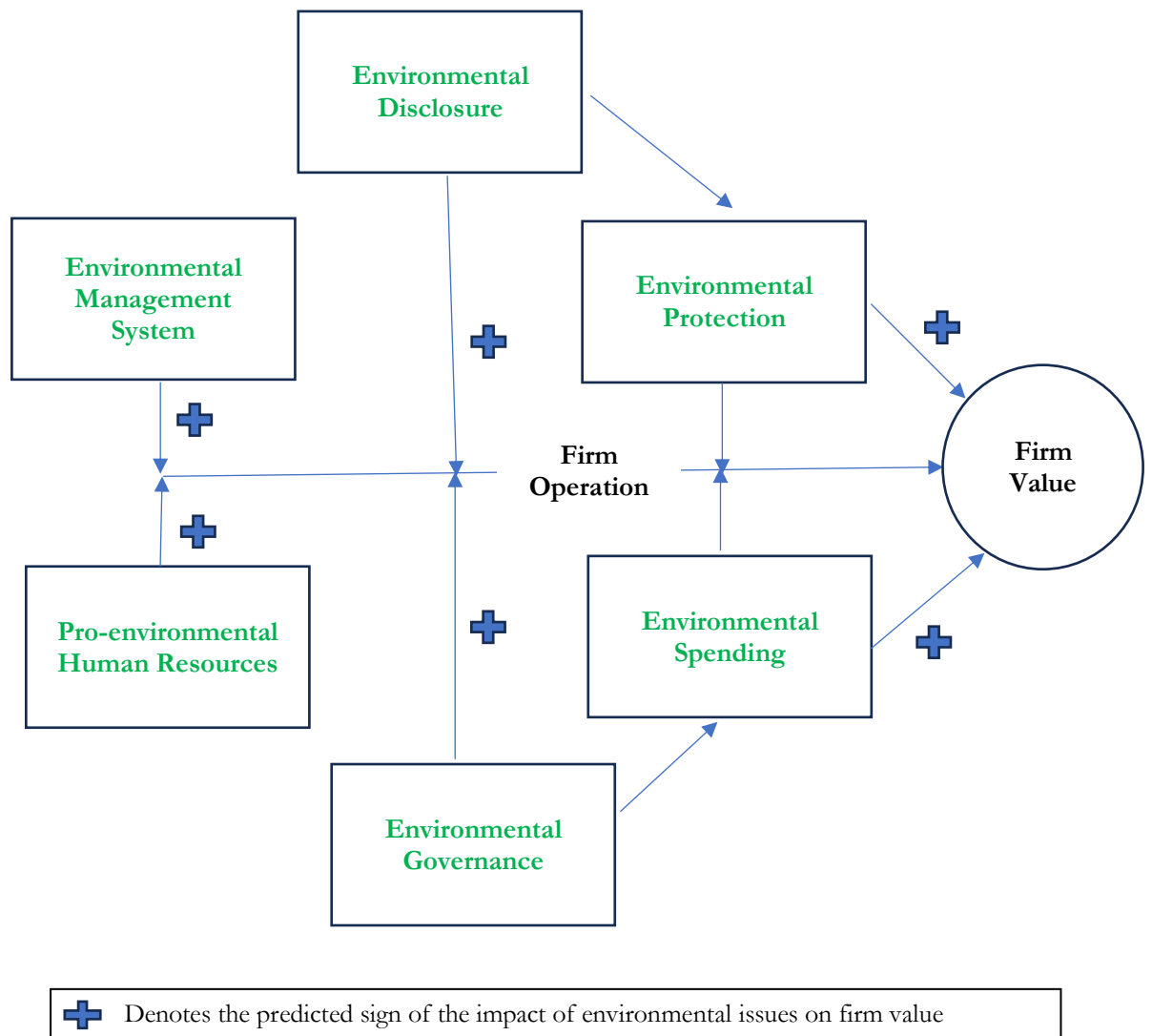
Model	Q1 (Low)		Q2 (Med)		Q3 (High)		(Q3-Q1)	
Panel A: Alphas based on value-weighted returns								
FF5	-0.554***	(-4.455)	-0.320**	(-2.285)	0.114	(1.171)	0.498***	(2.870)
FF6	-0.53***	(-4.386)	-0.315**	(-2.246)	0.127	(1.250)	0.495***	(2.844)
Panel B: Alphas based on equal-weighted returns								
FF5	-0.366***	(-3.799)	-0.105	(-1.393)	0.125	(1.416)	0.321**	(2.264)
FF6	-0.346***	(-3.660)	-0.093	(-1.192)	0.129	(1.450)	0.306**	(2.231)

Table 12 GC scores and future operating performance for non-financial firms

We conduct robustness check for the analysis in Table 6 by excluding financial stocks from the sample. This table reports results of non-financial stocks from regressing next-year operating performance on GC and a set of lagged predictive variables using industry-year fixed effect models. The dependent variable is Return on Assets (ROA) and Operating Profit Margin (OPM). The control variables are market beta (BETA), natural logarithm of market capitalization (SIZE), book-to-market ratio (BM), annual growth of book assets (AG), 11-month momentum returns (MOM), short-term return reversal (REV), idiosyncratic risk (IVOL), and annual stock turnover (ASTO). Columns (1) and (2) report the results where the dependent variable is ROA and Columns (3) and (4) report the results where the dependent variable is OPM. In Columns (2) and (4), we also add one-year lag of the firm's own ROA or OPM as control variables. T-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	(1) ROA _{t+1}	(2) ROA _{t+1}	(3) OPM _{t+1}	(4) OPM _{t+1}
GC _t	0.0120*** (6.105)	0.010*** (5.753)	0.0120*** (5.847)	0.001*** (4.605)
ROA _t		0.615*** (4.289)		
OPM _t				0.253 (1.093)
BETA _t	0.042*** (6.467)	0.027*** (3.702)	0.043*** (6.553)	0.032*** (2.882)
SIZE _t	0.006** (2.125)	0.001 (0.66)	0.007** (2.472)	0.003 (1.243)
BM _t	0.108** (2.529)	0.045 (1.462)	0.109** (2.553)	0.055 (1.255)
AG _t	0.024*** (4.601)	0.003 (.892)	0.025*** (4.728)	0.012 (1.129)
MOM _t	0.042*** (7.828)	0.021*** (10.924)	0.045*** (8.271)	0.031*** (2.921)
REV _t	0.120*** (4.825)	0.06*** (2.755)	0.127*** (5.088)	0.097*** (2.595)
IVOL _t	-0.193*** (-3.657)	-0.052 (-1.117)	-0.201*** (-3.796)	-.0102 (-1.288)
ASTO _t	-0.010*** (-4.472)	-0.005* (-1.866)	-0.010*** (-4.811)	-0.009*** (-2.758)
Intercept	-0.173** (-2.291)	-0.068 (-1.169)	-0.187** (-2.468)	-0.089 (-1.322)
Observations	22,785	22,785	22,785	22,785
Adj R ²	0.014	0.032	0.015	0.077
Industry F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y

Figure 1 Firm value implication for categories of Green Commitment (GC) index



Appendix 1 Environmental categories of GC Index

Details of the six environmental categories of the GC index, including design rationales and the selection of proxies, are described below.

(I) Presence of environment management system

This category focuses on whether firms have systematic procedures to manage environmental risks. We evaluate three distinct indicators based on company disclosures. (1) Disclosure of Establishing an Environmental Risk and Performance System. This indicator measures whether a firm has put in place a structured system to manage environmental risks and monitor performance. (2) Disclosure about Implementation of the ISO 14001⁸ System. We consider whether the firm has disclosed information about the adoption of the ISO 14001 standard, which requires establishment of an effective environmental management system. (3) Disclosure about Implementation of the ISO 9001⁹ System which pertains to quality management systems.

Research in operations management literature has consistently shown that firms implementing integrated management systems, including both ISO 9001 and ISO 14001, can persistently improve their performance even in dynamically changing environments (Hernandez-Vivanco et al., 2019; Wang & Liu, 2023). In the context of the Paris Agreement (formally adopted in 2015), investors and creditors in China have exerted pressure on firms to accelerate their transition toward a low-carbon economy. In 2016, the People's Bank of China, the Ministry of Finance, the National Development and Reform Commission, and four other ministries and commissions jointly released the “Guiding Opinions on Building a Green Financial System,” marking China's formal initiative to establish a comprehensive, multi-tiered green financial system (Huang et al., 2023). Green bonds are the most notable example of China's green financial system development. With virtually no issuances in 2015, the Chinese green bond market has

⁸ ISO 14001 is the internationally recognized standard for environmental management systems (EMS), which provides a framework for organizations to design and implement an EMS, and continually improve their environmental performance. (source: <https://www.iso.org/standard/60857.html>)

⁹ ISO 9001 is a globally recognized standard for quality management that helps organizations of all sizes and sectors to improve their performance, meet customer expectations and demonstrate their commitment to quality. (source: <https://www.iso.org/standard/62085.html>)

become one of the most active in the world by 2023.¹⁰

An effective operation management system can assist firms in meeting risk management requirements demanded by stakeholders through regular internal reviews and external audits (Power, 1999). Zhang (2023) has also utilized these three indicators to construct an environmental disclosure quality index. The reasoning behind this approach is that firms disclosing their management systems are less likely to engage in “greenwashing” activities, thus enhancing transparency and credibility.

(II) Pro-environmental human resource management

In this category, we examine whether firms implement pro-environmental human resource management (HRM) practices. These practices encompass various aspects, including environment-performance-based management systems, employee training related to environmental knowledge, and specific environmental projects with employee participation. A study by Marrucci et al. (2021), based on survey results of 819 EMAS¹¹-registered organizations, reveals that firms can enhance their operating performance by adopting green HRM practices. These practices include green recruiting, green training and involvement, and green performance management and rewarding. Notably, Daugaard (2020) highlights that existing ESG literature often overlooks the crucial role of employee participation.

(III) Disclosure of environmental spending

This category examines whether companies disclose their environmental spending, which encompasses various types of expenditures related to environmental initiatives. These include: (1) Environmental Investment, which covers expenses related to research and development (R&D) of environmentally friendly technologies. (2) Environmental Improvement expenses are associated with activities such as pollution restoration and environmental rehabilitation. (3) Environmental Innovation that includes technology development such as patents and innovations to enhance environmental performance. Martin & Moser (2016) find that managers disclose

¹⁰ <https://www.iflr.com/article/2d0tpxoec93sl0d7nsfeo/sponsored/green-finance-regulation-in-china>

¹¹ The Eco-Management and Audit Scheme (EMAS) is a voluntary environmental management process which enables organizations to assess, manage and continuously improve their environmental performance.

environmental spending because they recognize the societal benefits and anticipate positive reactions from investors. Furthermore, existing studies have highlighted the positive impact of environmental innovations on both carbon emission reductions and firm value (e.g., Hao et al., 2022; Qian et al., 2023; Wang et al., 2023; Xu et al., 2021).

(IV) Disclosure of environmental protection performance

In this category, we focus on firms' efforts toward environmental protection based on three indicators. The first is pollution under-emission, calculated based on residuals obtained from regressing the log value of carbon dioxide emissions against the log value of total sales¹². These regressions are performed at both industry and year levels. Firms with negative residuals are classified as those taking pro-environmental actions and receive a value of one. The second indicator is pollution reduction, defined as the annual change in carbon dioxide emissions. Firms that demonstrate reduced emissions are making pro-environmental efforts and thus receive a value of one. The third indicator focuses on energy savings reported by companies. When a company discloses specific values related to energy savings, it is awarded a value of one. Prior studies have utilized similar proxies in ESG rating metrics (Yang et al., 2024; Zhang, 2023).

(V) Credibility of environmental disclosures

This category centers around the credibility of environmental disclosures. Drawing from a sample of 4,645 firms across 49 countries or regions during the period from 2009 to 2019, Wen et al. (2022) observe that enhanced ESG disclosure quality has a positive impact on firms' market valuation and return on assets (ROA), while also mitigating downside risk. To assess disclosure quality, they employed the ESG disclosure quality metric provided by Sustainalytics. This metric evaluates a company's disclosure of ESG-related content and the degree to which the reporting aligns with best practices as per globally recognized sustainability reporting standards.

In our study, we adopt a similar approach to evaluate the credibility of environmental disclosures. Specifically, we classify firms that adhere to Global Reporting Initiative (GRI)¹³ reporting guidelines in their ESG/CSR disclosures as those actively pursuing

¹² Bolton & Kacperczyk (2021) use emission intensity as a proxy for carbon risk, which measures carbon emissions per unit of sales. Our approach follows their logic and controls for the industry effect.

¹³ The Global Reporting Initiative (GRI) is an international independent organization that helps

pro-environmental actions. These firms receive a value of one and zero otherwise.

Existing research also highlights that ESG disclosures that are assured by third-party agencies or professionals contribute to corporate reputation and reduce ESG rating disagreements (Kimbrough et al., 2024; Simnett et al., 2009). Consequently, we also evaluate the quality of environmental disclosures based on the presence of external assurance. Specifically, we assign a value of one to firms that have ESG/CSR reports certified by independent agencies. Additionally, we award a dummy value of one to firms whose accounts are audited by one of the Big 4 auditors and zero otherwise.

Finally, we examine whether firms disclose internal control system deficiencies. Previous research suggests that quality of reporting improves significantly by including voluntary disclosure of internal control weaknesses in both the US and China (Ashbaugh-Skaife et al., 2009; Ji et al., 2017). If a firm discloses an internal control system deficiency, it is given a value of one, otherwise zero.

(VI) Effectiveness of environmental governance

This category focuses on both internal and external governance related to environmental matters. Previous studies have consistently highlighted the strong connection between experience and job performance (Dokko et al., 2009). In a survey of CEOs at Danish firms, Amore et al. (2019) find that highly educated CEOs express greater concerns about climate change, leading them to take more sustainable corporate actions. Additionally, research by Cosma et al. (2021) using survey data on Italian board members reveals that the personal attributes of board members significantly influence their attitudes toward environmental protection. For example, members of the risk committee tend to exhibit stronger environmental attitudes. In an online simulation experiment conducted by Tomlinson et al. (2020), human participants were assigned roles as corporate directors. Some were informed they were nominated by shareholders, others by employees, and some via a vote by a committee of environmental scientists. The results demonstrate that directors selected by environment scientists showed balanced preferences across stakeholder groups, behaving notably differently from both

businesses, governments and other organizations understand and communicate the impact of businesses on critical sustainability issues such as climate change. GRI provides Guidelines that reflect the perspective of a diverse range of stakeholders that are aiming at transparency.

shareholder-selected directors and employee-selected directors.

These findings underscore the importance of considering diverse perspectives and personal attributes when shaping environmental policies and corporate behavior. By understanding how different stakeholders perceive environmental issues, organizations can make informed decisions that benefit both the environment and society as a whole. Based on the extant literature, we propose that senior managers and directors who have environmental expertise or experience will be more cautious about the environmental implications of corporate decisions and monitor the environmental impacts of corporate actions more closely. We collect management and director profiles and conduct textual analysis to determine whether they have study or work experience in environmental areas. There are three dummy variables for the presence of ‘green’ executive directors, independent directors, and senior managers. For the presence of each, we assign a value of one to a firm and zero otherwise.

In recent years, the influence of institutional investors on environmental, social, and governance (ESG) matters has gained prominence. Notably, green institutional investors—those who prioritize sustainability and maintain a long-term investment horizon—have been associated with positive impacts on firms’ ESG performance (Chen & Xie, 2022; Liu et al., 2023). In this context, we consider the presence of ‘green’ institutional investors within companies as the final indicator for this category.

To identify ‘green’ investors, we merge two datasets: information on each fund’s investment objectives and scope in the Chinese fund market and data on the fund’s shares in listed companies. A fund qualifies as a green investor if its investment objectives or scope explicitly include keywords related to environmental sustainability, such as “ecology,” “renewable,” “recycling,” “low carbon,” “green energy,” “water conservation,” and “environmental quality.” When a firm discloses the share ownership by green institutional investors, it receives a value of one. This approach is consistent with previous research by Chen & Xie (2022) who also treat the presence of green institutional investors in similar ways.

Appendix 2: Green Commitment Data Collection

In this appendix, we outline the process used to collect and analyze data on the green commitment (GC) of listed A-share companies in China. We initially use environmental data from CSMAR and CNRDS. When specific data items are not available, we supplement this with manual data collection. The primary sources of data collection include annual reports, Corporate Social Responsibility (CSR) reports¹⁴, and voluntary management reports on internal control. These documents were obtained from CNINFO (www.cninfo.com.cn)¹⁵, the Shanghai Stock Exchange (www.sse.com.cn), the Shenzhen Stock Exchange (www.szse.cn), and company websites. As most reports are fiscal-year-end documents, the GC index data are compiled on an annual basis.

For most environmental categories in the GC index, proxy values are determined by the presence of relevant keywords in the downloaded company reports. The keywords listed in the document are English translations of Chinese words used during data collection. For example, the adoption of the ISO 14001 environmental management quality system can be confirmed if the keyword search in the CSR report returns a positive result. Keywords for this include “ISO 14001” and “environmental management quality system.”

When company reports are not available from the specified websites, we use internet search engines to check if company announcements contain the required green commitment data. If no information about a particular proxy is found, the proxy value is set to zero.

For some environmental categories of the GC index, the proxy values rely on reported environmental protection performance data, such as carbon dioxide emissions, energy consumption, and pollution. We search the company reports for relevant keywords and store the texts containing these keywords along with the corresponding numeric values.

¹⁴ In our data collection, CSR Reports encompass Corporate Social Responsibility Reports, Sustainability Reports, and ESG Reports, as these terms are used interchangeably by Chinese listed firms to present their environmental performance.

¹⁵ www.cninfo.com.cn is the information disclosure website for listed companies designated by the China Securities Regulatory Commission. Established in 1995, it is the earliest professional securities information website in the country. It is also the first large-scale professional securities website in China to comprehensively disclose announcements and market data of all listed A-share stocks.

These texts are subsequently processed by text analysis codes and manually inspected to determine the reported performance values. Appendix 3 provides sample codes to illustrate the extraction of carbon dioxide emission data from CSR reports, serving as an example of our data collection procedure for environmental performance data.

For environmental patent and innovation proxy and environmental governance proxies, we use the relevant records from the Chinese Research Data Services Platform (CNRDS) and CSMAR, separately.

(I) Presence of Environmental Management System

Information on the presence of an environmental management system is extracted from CSR reports. Keyword searches are used to identify relevant information, with exemplar keywords including:

- “environmental risk management”
- “environmental performance management”
- “ISO 14001”
- “environmental management quality system”
- “ISO 9001”
- “quality management system”

(II) Pro-Environmental Human Resource Management

Data on pro-environmental human resource management are also extracted from CSR reports using keyword searches. Key terms include:

- “ESG talent development”
- “environmental performance reward”
- “ESG performance management”
- “sustainability performance management”
- “environmental knowledge training”
- “ESG training”
- “ISO 9001”
- “Quality Management System”

(III) Disclosure of Environmental Spending

Environmental spending information is collected from company reports and the China National Intellectual Property Administration. For environmental investments and improvement expenses, annual reports and CSR reports are searched using keywords such as:

- “environmental investment”
- “environmental protection R&D”
- “sewage charge”
- “environment protection fee”
- “fees for provision of areas of greenery”
- “environmental expenditure”

For green innovation data, firm-level information about green patents and innovations is gathered from the Chinese Research Data Services Platform (CNRDS), a comprehensive data platform for research in China's economy, finance, and business.

(IV) Disclosure of Environmental Protection Performance

Environmental protection performance data are extracted from CSR reports. For carbon dioxide emissions, relevant keywords include:

- “carbon dioxide emission”
- “CO2 emission”
- “greenhouse gas emission”
- “GHGs emission”

Total sales data are based on Total Operating Revenue (data item: B001100000)¹⁶ provided by CSMAR. Under-emission is calculated as the residual from a regression of the log value of emissions on the log value of sales, with industry and year fixed effects, addressing systematic differences in operating characteristics between industries. Pollution reduction measures are assessed by extracting annual pollution-level data from CSR reports with keywords such as:

¹⁶ In CSMAR, Total Operating Revenue (B001100000) = Operating Revenue + Net Interest Income + Earned Premiums + Net Fee and Commission Income + Other Business Income. The Total Operating Revenue data is hence available for both financial and non-financial firms.

- “total pollutant emission”
- “total pollution emission”
- “total amount of waste”

The year-to-year change in pollution measures determines whether there is a reduction. Energy-saving measures are evaluated by extracting energy consumption data from CSR reports using keywords such as:

- “total energy consumption”
- “total energy expenditure”
- “power usage”

The year-to-year change in energy consumption measures indicates reductions.

(V) Credibility of Environmental Disclosures

The credibility of environmental disclosures is examined using information from CSR reports and CSMAR. For adherence to GRI standards, keyword searches include:

- “GRI”
- “Global Reporting Initiative”
- “sustainability reporting standards”

For external assurance, keywords are:

- “third party assurance”
- “third party certification”

The presence of Big 4 auditors is verified using auditor names provided in the Audit Opinion database in CSMAR. Voluntary management reports on internal control are examined for internal control system deficiencies.

(VI) Effectiveness of Environmental Governance

The effectiveness of environmental governance is assessed using the corporate governance database in CSMAR, which provides background information on directors and managers of listed firms. Management and director profiles are searched with keywords such as:

- “environmental protection”
- “environmental management”
- “environmental governance”
- “ESG management”

The presence of green institutional investors is identified using the mutual fund database in CSMAR, which includes information on the investment objectives and shareholding position details of mutual funds. We define a mutual fund as a green investor if its investment objectives or scope explicitly include keywords related to environmental sustainability:

- “ecology”
- “renewable”
- “recycling”
- “low carbon”
- “green energy”
- “water conservation”
- “environmental quality”

Appendix 3: Green Commitment Data Extraction Code Examples

In this appendix, we provide sample codes to illustrate the process of downloading company reports and extracting carbon dioxide emissions information using the R language packages ‘pdftools’ and ‘pdfsearch’. The following two code examples demonstrate the task performed for Shenzhen Development Bank from the CNINFO website and that for Postal Savings Bank from the company's website, respectively.

In the first instance, we utilize the R programming language to extract carbon dioxide emissions data for the year 2010 pertaining to Shenzhen Development Bank (currently Ping An Bank, stock code: 000001) from the CNINFO website. Specifically, we use the ‘pdf_text’ function to convert the downloaded file into text data and the ‘keyword_search’ function to extract text containing the relevant keyword “carbon dioxide emissions”.

The information extracted is translated into English and provided below for illustration. The text contains two important aspects of CO₂ emissions data: Section [2] presents the annual CO₂ emissions data, while Section [3] provides the formula employed by Shenzhen Development Bank to report annual CO₂ emissions, which is based on electricity usage.

“[2] (II) CO₂ Emissions

Time: 2010, 2009, 2008

CO₂ emissions from energy consumption: approximately 3,487,017 (2010), approximately 2,933,368 (2009), approximately 2,880,816 (2008) (unit: kg)

CO₂ emissions from vehicle travel: approximately 339,120 (2010), approximately 254,340 (2009), approximately 218,544 (2008) (unit: kg)

Total (unit: kilotons): approximately 3,826 (2010), approximately 3,188 (2009), approximately 3,318 (2008)

Note: The CO₂ emission data from energy consumption covers the self-owned properties in the Shenzhen area, and the CO₂ emission data from vehicle travel covers the self-owned vehicles of the head office.

[3] According to the energy conversion data published by the country, the carbon dioxide conversion formula is: consumption of 1 degree of electricity = emission of

0.997 kg of carbon dioxide; the carbon dioxide emission (kg) from vehicle travel = fuel consumption in liters $\times$ 0.785.”

In the second instance, we apply the R programming language to extract carbon dioxide emissions data for the year 2018 for the Postal Savings Bank (stock code: 601658). For this case, we use the keyword “Greenhouse Gas Emissions” instead of “CO2 Emissions” because companies use these words interchangeably during the sample period. The extracted text is translated into English and provided below.

“Low-carbon environmental protection, builders of beautiful China

Emissions in 2018, Environmental Performance Indicators

Sulfur dioxide (tons)¹: 0.01

Nitrogen oxides (tons)²: 0.71

Total greenhouse gas emissions (Category 1 and Category 2) (tons)³: 123,383.73

Environmental Performance

Per capita greenhouse gas emissions (Category 1 and Category 2) (tons/person): 6.89

Greenhouse gas emissions per square meter of floor area (Category 1 and Category 2) (tons/square meter): 0.17

Unless otherwise stated, the scope of environmental performance statistics in this section includes the head office of China Post Savings Bank 1 and the domestic first-level branch offices.”

Appendix 4: Variable definitions

Table A.1 Definitions of variables

This table gives definitions of independent variable, dependent variables, mechanism variables, and control variables as well as the predicted signs of variables in explaining future stock returns.

Variable	Definition	Pred. Sign
Panel A Independent variable		
GC	Green Commitment index derived from 20 scoring items on environment issues, gauging a firm's environmental commitment.	+
Panel B Dependent variable		
RET	(Ending Stock Price – Beginning Stock Price)/Beginning Stock Price.	
ROA	Net profit divided by book value of total assets.	
OPM	Operating profit scaled by sales.	
Panel C Constraints variable		
KZ	Financial constraints index proposed in Kaplan & Zingales (1997) which is computed as follows: $KZ_{i,t} = -1.002 \times \frac{CF_{i,t}}{Assets_{i,t-1}} + 0.283 \times Q_{i,t} + 3.139 \times \frac{Debt_{i,t}}{Assets_{i,t}} - 39.368 \times \frac{DIV_{i,t}}{Assets_{i,t-1}} - 1.315 \times \frac{Cash_{i,t}}{Assets_{i,t-1}}$ where CF is cashflow, Assets is total assets, Q is Tobin's Q, Debt is total debt, DIV is dividends, Cash is cash and equivalents.	-
WW	Financial constraints index proposed in Whited & Wu (2006) which is computed as follows: $WW_{i,t} = -0.091 \times \frac{CF_{i,t}}{BA_{i,t-1}} - 0.062 \times DIVPOS_{i,t} + 0.021 \times \frac{LD_{i,t}}{CA_{i,t}} - 0.044 \times LNTA_{i,t} - 0.035 \times SG_{i,t} + 0.102 \times ISG_{i,t}$ where BA is total assets, DIVPOS is dividend dummy variable. LD is long-term debt, CA is the current assets, LNTA is the logarithm of total assets, SG is sales growth and ISG means industrial sales growth.	-
Panel D Control variable		
BETA	Market beta of a firm based on one-year stock returns.	+
SIZE	Natural logarithmic of a firm's market capitalization.	
BM	Book-to-market ratio.	+
AG	Annual growth rate of book value of total assets.	
MOM	The 11-month return momentum, skipping the most recent month.	+
REV	Return reversal measured as stock returns in the most recent month.	-
IVOL	Idiosyncratic risk measured as the standard deviation of residuals from the Fama-French three-factor model.	-
ASTO	Annual share turnover.	-