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## **E Rating and Carbon Risk Premium: Evidence from the Chinese Stock Market**

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### **Abstract**

This paper measures enterprises' carbon risk based on the E rating (environmental rating) of A-share listed companies from 2009 to 2020. Through two methods—constructing simulated portfolios and directly regressing company characteristics on stock returns—we demonstrate that a reversal in the sign of the carbon premium occurred in China's A-share market during 2015-2016. The results show that during 2013-2015, China's A-share market exhibited a significant carbon risk premium, whereby non-green companies with low E ratings had higher average monthly returns compared to green companies with high E ratings; during 2016-2020, green companies instead had higher average monthly returns. Further investigation reveals that the reversal in the sign of the carbon premium is highly correlated with the implementation of green finance policies.

### **Full Text**

#### **E Ratings and Carbon Risk Premium: An Empirical Study Based on China's Stock Market**

This paper examines carbon risk faced by listed companies in China's A-share market using E ratings (environmental ratings) from 2009 to 2020. Through two methodologies—constructing mimicking portfolios and regressing stock returns directly on firm characteristics—we demonstrate that a structural shift in the sign of the carbon premium occurred in China's A-share market during 2015-2016. The results show that during 2013-2015, China's A-share market exhibited a significant positive carbon risk premium, where low-E-rated non-green companies achieved higher average monthly returns than high-E-rated green companies. During 2016-2020, however, green companies achieved higher average monthly returns. Further investigation reveals that this shift in the sign of the carbon premium is highly correlated with the implementation of green finance policies.

**Keywords:** carbon risk premium; green incentive; green finance; environmental, social, and governance (ESG); excess return

Since the reform and opening-up, China's economy has experienced over 40 years of quantitative high-speed growth, effectively meeting people's material and cultural needs. However, the traditional extensive development model now faces sustainability and efficiency challenges, necessitating a transformation toward sustainable economic development. In September 2010, the State Council officially released a document proposing to accelerate the cultivation and development of the energy conservation and environmental protection industry along with seven other strategic emerging industries. On December 10, 2013, during the Central Economic Work Conference, General Secretary Xi Jinping first proposed the "new normal" concept. In April 2015, the Central Committee of the Communist Party and the State Council issued the "Opinions on Accelerating the Construction of Ecological Civilization," marking the beginning of China's green finance development. On September 21, 2015, the Central Committee and the State Council printed and distributed the "Overall Plan for Ecological Civilization System Reform," which first clarified the top-level design of China's green financial system (Ma Jun, 2016). In November 2015, the Ministry of Commerce announced that total social investment in energy conservation and environmental protection during the 13th Five-Year Plan period was expected to exceed 17 trillion RMB. In December 2015, the Paris Agreement was adopted at the 21st United Nations Climate Change Conference (Paris Climate Conference), and China signed it on April 22, 2016. On March 16, 2016, the 13th Five-Year Plan explicitly proposed establishing a green financial system, developing green credit and green bonds, and establishing green development funds.

On August 31, 2016, the People's Bank of China and six other ministries jointly issued the "Guiding Opinions on Establishing the Green Financial System," clarifying the policy framework for green finance development. Thus, 2015-2016 represents a critical period for establishing China's green financial system, laying its foundation and outlining its blueprint.

Carbon risk typically refers to risks associated with climate change or fossil fuel usage (Hoffmann & Busch, 2008). A positive carbon risk premium generally means that non-green enterprises face greater carbon risk than green enterprises, resulting in higher stock returns, while a negative carbon premium indicates the opposite. As a crucial component of the green financial system, capital markets' ability to correctly identify corporate carbon risk and provide corresponding risk compensation to investors concerns market efficiency and corporate financing efficiency. For investors, understanding return and risk differences between green and non-green companies can improve investment outcomes.

Against this background, this paper uses data from A-share listed companies from 2009-2020, combined with China Securities Index (CSI) E rating data, to investigate the existence and sign of the carbon premium. Empirical results show that China's A-share market experienced a shift in carbon risk premium from positive to negative during 2015-2016. During 2013-2015, the A-share

market exhibited a significant positive carbon premium; during 2016-2020, it exhibited a significant negative carbon premium.

This paper's potential marginal contributions are threefold: First, using systematically standardized E ratings from third-party information companies to measure listed companies' carbon risk exposure yields more accurate empirical results. Second, empirical evidence shows that the sign of the carbon premium can shift, and this shift is temporally consistent with green finance policy implementation, helping evaluate green financial system development. Third, proving the existence of a carbon premium assists investors in their investment activities.

## Literature Review

Since Fama & French (1993) proposed the three-factor model, numerous risk factors have been discovered and confirmed by scholars. With the outbreak of environmental events such as global warming, investors' environmental awareness has gradually increased, and they have begun paying attention to environmental risks faced by listed companies. In recent years, ESG (Environmental, Social, and Governance) investment strategies have also gained widespread market attention. As environment is a crucial component of ESG evaluation systems, we must also examine research on ESG risk premiums.

Currently, two mainstream views exist regarding carbon risk faced by listed companies:

First, a negative carbon risk premium exists in capital markets. Green enterprises, such as those in the new energy sector, face greater technological development risks compared to traditional energy industries, and changes in energy conservation and emission reduction policies can significantly impact these enterprises' future cash flows. This negative carbon risk premium is also called a green incentive (Han Liyan et al., 2017). Atan et al. (2018) found that Malaysian companies' ESG scores are positively correlated with weighted average cost of capital. Liu Yong and Bai Xiaoying (2020), based on Hexun's ESG ratings, confirmed that Chinese institutional investors have significant ESG investment preferences, and stocks with higher ESG ratings have higher returns.

Second, a positive carbon risk premium exists in capital markets. Non-green enterprises, such as traditional chemical industries, also face energy conservation and emission reduction policies that may restrict pollutant emissions and force technological innovation. These risks are typically called positive carbon risk premium, or simply carbon premium. Oestreich and Tsiakas (2015) used the EU Emissions Trading Scheme to empirically find that German stocks receiving free emission allowances significantly outperformed those without free allowances, with the carbon premium including both cash flow effects from free emission rights and carbon risk factors. Bolton and Kacperczyk (2021) found that U.S. stockholders already demand premium compensation for holding non-green stocks. Di Luo (2022) discovered significant ESG premiums in the UK stock market in an empirical study, with significance negatively correlated with

stock liquidity. Wei Ping and Shu Hao (2018) found that green fund investment performance in China is significantly lower than the market average. Li Jin (2021), using ESG data from multiple rating agencies from 2015-2020 and constructing a four-factor model, found significant ESG risk premiums in China's A-share market. Qiu Muyuan and Yin Hong (2019), using Bloomberg ESG scores, found that improved ESG scores can reduce financing costs and increase market valuation, with environment and corporate governance having greater impacts on financing costs.

These two views are not entirely contradictory. At different market development stages, one risk premium may dominate asset pricing. For example, the U.S. market carbon risk premium evolved from insignificant to significant (Bolton and Kacperczyk, 2021), while China's stock market experienced a shift from green incentive to carbon premium during 2013-2014 (Han Guowen and Fan Chengheng, 2021).

Additionally, some scholars believe that investors' preferences for green enterprises may also affect portfolio risk-adjusted returns (Pedersen et al., 2021). Wei Ping and Shu Hao (2018) found that Chinese green funds' risk-adjusted returns are lower than market benchmarks.

## Research Design

### Sample Selection and Data Sources

This paper selects monthly and quarterly data from April 2009 to January 2021 for 4,412 individual stocks in the A-share market as the research sample. Monthly frequency data is used in the three-factor and four-factor model sections, totaling 310,993 observations; quarterly frequency data is used in OLS regressions verifying carbon premium sign, totaling 108,376 observations. Both datasets undergo the following processing: (1) excluding ST, \*ST stocks and financial industry stocks; (2) excluding stocks listed for less than half a year; (3) excluding stocks with negative book value.

Individual stock E rating data comes from Shanghai China Securities Index Information Service Company, individual stock Beta data from RESSET Database, stock returns and financial data from CSMAR Database, and "green finance" search index from Baidu Index.

### Selection of Carbon Risk Measurement Indicators

Lash & Wellington (2007) early defined carbon risk, arguing it includes three independent but related risk components: regulatory risk, physical risk, and business risk, which can be divided into six specific risks: regulatory risk, physical risk, reputational risk, legal risk, product and technology risk, and supply chain risk (Zhang Xueyong and Liu Qian, 2022).

ESG is the English abbreviation for Environmental, Social, and Governance, typically referring to value concepts, investment strategies, and evaluation tools

that focus not only on corporate financial performance but also on environmental, social, and corporate governance performance. ESG indicators are important metrics for assessing corporate sustainable development capabilities (Cao Qun and Xu Qian, 2019).

Since the United Nations Principles for Responsible Investment (PRI) were proposed in 2006, the ESG concept has been clarified and flourished in developed markets, with ESG rating agencies rapidly increasing. By 2021, the number of global ESG rating agencies exceeded 600 (Wang Kai and Zhang Zhiwei, 2022).

China's ESG concept development can be traced back to the 2008 "Notice on Strengthening Listed Companies' Social Responsibility" issued by the Shanghai Stock Exchange, which explicitly required listed companies to disclose specified environmental information. In 2012, the Hong Kong Stock Exchange released the "Environmental, Social and Governance Reporting Guide," further clarifying disclosure indicators. Until 2015, when China explicitly established a green financial system, ESG investment began to develop rapidly in China, and a batch of ESG rating agencies targeting China's A-share market emerged. Currently, China's major ESG rating agencies include China Securities Index, Syn-Tao Green Finance, Social Investment Alliance, and the Green Finance Research Institute of Central University of Finance and Economics.

Selecting a reasonable indicator to measure corporate environmental performance is key to correctly identifying carbon risk premium. China Securities Index publishes quarterly sub-rating data for all A-share listed companies, with ratings traceable to 2009, covering the broadest range among domestic indices with relatively detailed indicators.

China Securities Index E rating sets 5 secondary indicators and 17 tertiary indicators, with quantitative indicators accounting for 70%. It uses carbon emissions as the most important factor for measuring climate change indicators, similar to Bolton and Kacperczyk (2021)'s method for measuring carbon risk, offering high comparability. Additionally, China Securities Index E rating also focuses on multiple indicators including corporate environmental development goals disclosure, resource consumption, environmental management level, and environmental friendliness capabilities, corresponding to the six specific risks proposed by Lash & Wellington (2007), fully measuring corporate carbon risk exposure.

In summary, we select China Securities Index E rating as the proxy variable for measuring corporate carbon risk exposure. China Securities Index E rating is published four times annually on January 31, April 30, July 31, and October 31, which this paper uses to define quarters.

## Empirical Models and Variable Definitions

**1. Factor and Mimicking Portfolio Construction** This paper first follows Fama & French (2015) and Han Liyan et al. (2017) to sort individual stocks

and construct asset pricing factors, demonstrating that the green factor has significant pricing power.

Factor construction methods are as follows: (1) Market factor MKT: Calculate the average of individual stock monthly returns with dividend reinvestment weighted by circulating market capitalization, then subtract the risk-free rate. The risk-free rate is the geometric average of one-year Chinese government bond yields from the China Central Depository & Clearing Co. database. (2) Size factor SMB (dichotomy) and book-to-market ratio factor HML (trichotomy): First, sort individual stock monthly returns from May of year  $t$  to April of year  $t+1$  by circulating market capitalization at the end of April of year  $t$ , and obtain the 50th percentile, where stocks above the 50th percentile are recorded as group B and those below or equal as group S. Then, sort stock returns from May to December of year  $t$  by book-to-market ratio at the end of the previous fiscal year, and take the 30th and 70th percentiles, where stocks above the 70th percentile are recorded as group H, those between 30th and 70th percentiles as group M, and those below the 30th percentile as group L. Cross-combining circulating market capitalization groups and book-to-market ratio groups yields six stock portfolios: BH, BM, BL, SH, SM, SL. Portfolio monthly returns are calculated as the circulating market capitalization-weighted average within each portfolio. (3) Green factor GMNG (trichotomy): To fully utilize quarterly data, each quarter individual stock E rating data is sorted from high ratings (AAA rated as number 9) to low ratings (C rated as number 1). Stocks with E ratings above the 70th percentile are recorded as group G, those below or equal to the 70th percentile but above the 30th percentile as group MG, and those below or equal to the 30th percentile as group NG. Combined with the above groupings by circulating market capitalization and book-to-market ratio, 18 groups are obtained: BHG, BHNG, BMG, BHM, BMM, BLM, BMNG, BLG, BLNG, SHG, SHNG, SMG, SHMG, SMM, SLMG/SMHG, SLG, SLHG. Portfolio monthly returns are calculated as the circulating market capitalization-weighted average within each portfolio. For robustness, we also group by the 50th percentile, recording stocks with E ratings above the 50th percentile as group G and those below or equal as group NG, denoted as green factor GMNG (dichotomy), with results shown in the robustness tests.

Factor calculation methods are as follows:

In the four-factor model, mimicking portfolio construction is similar to factor construction. First, individual stock monthly returns from May of year  $t$  to April of year  $t+1$  are divided into 16 groups based on circulating market capitalization and book-to-market ratio at the end of April of year  $t$ . Both circulating market capitalization and book-to-market ratio use quartile grouping, i.e., divided into 4 groups based on the 25th, 50th, and 75th percentiles, then cross-combined. Then, all individual stocks at the same time point are grouped by the most recent quarterly E rating data using the trichotomy method. Results for mimicking portfolios constructed using the dichotomy method for E rating are shown in the robustness test section.

Through the above steps, 48 portfolio groups are obtained, and the circulating market capitalization-weighted average monthly excess returns of the 48 portfolio groups are calculated.

## 2. Green Factor Pricing Power and Carbon Premium Sign Model

After constructing factors and portfolios, the following model tests factor significance:

Where is the dividend reinvestment return of stock  $i$  in month  $m$  of year  $t$  minus the risk-free rate, is the monthly excess return of the constructed mimicking portfolio. The values represent the overall sensitivity of all market assets to each factor, or factor exposure/factor loading. Values significantly different from zero and factor returns significantly different from zero indicate that the corresponding factor has significant pricing power.

In addition to the above model, following Bolton and Kacperczyk (2021), we use OLS regression of firm characteristics and individual stock returns to analyze the carbon premium sign issue in China's market. For convenience, the following individual stock quarterly data regression model is referred to as OLS regression hereafter.

Where is the dividend reinvestment return of stock  $i$  in quarter  $q$  of year  $t$ , is the E rating of stock  $i$  at the beginning of quarter  $q$  in year  $t$ , and is the control variable. Control variables are selected following Bolton and Kacperczyk (2021), with details shown in Table 1. If is significantly positive, it indicates a significant negative carbon risk premium in the A-share market during the sample period; if significantly negative, it indicates a significant positive carbon risk premium.

Variable definitions are shown in Table 1 below.

**Table 1 Main Variable Definitions**

Variable Name	Frequency	Definition
Individual stock monthly excess return	Monthly	Individual stock monthly return - risk-free rate
Portfolio monthly excess return	Monthly	Portfolio monthly return - risk-free rate
Risk-free rate	Monthly	Geometric average of 1-year Chinese government bond yields from China Central Depository & Clearing Co.
Market factor	Monthly	Market capitalization-weighted average return - risk-free rate

Variable Name	Frequency	Definition
Size factor SMB	Monthly	Return of going long small-cap and short large-cap stocks
Book-to-market factor HML	Monthly	Return of going long high book-to-market ratio and short low ratio stocks
Green factor GMNG (dichotomy)	Monthly	Return of going long high E rating and short low E rating stocks
Green factor GMNG (trichotomy)	Monthly	Return of going long high E rating and short low E rating stocks
Individual stock quarterly return	Quarterly	Dividend reinvestment quarterly return, Q1 defined as Feb 1-Apr 30
E rating	Quarterly	China Securities Index ESG rating sub-data, C=1, AAA=9
Book-to-market ratio	Quarterly	Book-to-market ratio from most recent financial report
Fixed assets net value	Quarterly	Natural log of fixed assets net value (thousand RMB) from most recent financial report
Leverage	Quarterly	Asset-liability ratio from most recent financial report
Sales growth	Annual	Sales growth rate from most recent annual report
EPS growth	Annual	Earnings per share growth rate from most recent annual report
ROE	Quarterly	Return on equity from most recent financial report

Variable Name	Frequency	Definition
Beta	Quarterly	Standard deviation of daily returns over past 240 days, calculated with 240-day circulating market capitalization weighting
Momentum	Quarterly	Dividend reinvestment return over past year before E rating date
Market cap	Quarterly	Natural log of most recent circulating market capitalization (thousand RMB)

**3. Data Processing and Descriptive Statistics** When empirically studying the carbon premium sign through OLS regression, some financial data (Bm, Ppe, Leverage, and Roe) are matched with the most recent available financial report data relative to the E rating date, denoted as matching method 1. This matching method can better utilize disclosed information, but whether listed companies choose to disclose quarterly reports may correlate with certain firm characteristics, posing potential selection bias risks. Therefore, this paper also uses matching method 2, i.e., matching with the most recent annual report data, for robustness tests. Regression results from both matching methods are consistent, with details shown in the robustness test section. A detailed comparison of matching methods is shown in Table 2 .

**Table 2 Matching Methods Summary**

E Rating Date	Matching Method 1	Matching Method 2
Jan 31, Year T	Match T-1 semi-annual report	Match T-2 annual report
Apr 30, Year T	Prefer T Q1 report, alternatively T-1 annual report	Match T-1 annual report
Jul 31, Year T	Prefer T Q1 report, alternatively T-1 annual report	Match T-1 annual report
Oct 31, Year T	Prefer T Q3 report, alternatively T-1 semi-annual report	Match T-1 annual report

When studying the carbon premium sign through OLS regression, to reduce

outlier effects, this paper applies 1% winsorization to individual stock quarterly returns, Beta, book-to-market ratio, momentum, leverage ratio, and ROE, and 2.5% winsorization to sales growth and EPS growth, which have more outliers.

Descriptive statistics for main variables are shown in Table 3 . The factor model descriptive statistics show that mimicking portfolio returns have smaller standard deviations than individual stock returns, indicating that diversified investment reduces idiosyncratic risk. The market factor has a mean of 0.92, and the size factor has a mean of 0.20, suggesting small-cap stocks generally have higher returns. Both dichotomy and trichotomy green factors have monthly average returns of 0.04, with the trichotomy factor having slightly larger standard deviation. The OLS regression descriptive statistics show that the median E rating is 1, with over 50% of listed companies having the lowest C rating, and the 75th percentile is 3. Therefore, the green factor in most years actually represents returns from holding stocks rated above C and shorting stocks rated C. Due to the special distribution of E ratings, the trichotomy green factor may better capture return differences between green and non-green companies.

### Table 3 Descriptive Statistics for Main Variables

*Note: All data above use circulating market capitalization weighting.*

ADF test results for time series variables are shown in Table 4 . All factors pass the ADF test at the 1% significance level, indicating they are stationary time series without pseudo-regression problems.

### Table 4 ADF Test for Factors

Factor	Circulating Market Cap Weighted	ADF Statistic
Market		-6.10

## Empirical Results and Analysis

### Three-Factor Model

Table 5 shows the average monthly returns of 16 mimicking portfolios grouped by circulating market capitalization and book-to-market ratio during 2009-2020. As shown, except for the lowest book-to-market ratio group, small-cap stocks in other groups have higher average returns than large-cap stocks, with clear monotonicity of decreasing returns with increasing market capitalization, consistent with the three-factor model conclusions. However, high book-to-market ratio stocks do not show obvious risk premiums, with no clear relationship between book-to-market ratio and portfolio average monthly returns after controlling for circulating market capitalization.

### Table 5 Full Sample Monthly Average Returns of 16 Portfolios Grouped by Circulating Market Cap and Book-to-Market Ratio (%)

Table 6 presents three-factor model regression results for various portfolios and individual stocks during 2009-2020. Columns (1)-(3) show portfolio regression results, columns (4)-(6) show individual stock regression results. Column (1) shows green portfolio results, column (2) non-green portfolio results, column (3) all portfolio results, column (4) green individual stock results, column (5) non-green individual stock results, and column (6) all individual stock results. All six columns use panel regression. Hausman test results significantly reject the random effects model. To control for residual correlation as much as possible, columns (4)-(6) control for individual stock fixed effects, and all subsequent individual stock regressions control for individual stock fixed effects.

Overall, the three-factor model has good explanatory power for cross-sectional differences in China's stock returns. All portfolio regression column (3) and all individual stock regression column (6) show significant factor coefficients, with market factor MKT and size factor SMB coefficients significantly positive, and book-to-market factor HML coefficient significantly negative. Columns (1) and (2) show insignificant HML factors, related to smaller sample sizes. In columns (1), (3)-(6), constant terms are significantly non-zero, indicating the three-factor model cannot fully explain excess returns in China's A-share market, and other undiscovered factors remain. Comparing portfolio and individual stock regression results shows highly consistent coefficients.

#### **Table 6 Three-Factor Model Regression Results**

*Note:* , , \* indicate significance at 1%, 5%, and 10% levels respectively. All regressions use clustered robust standard errors.\*

#### **Green Factor Pricing Power—Four-Factor Model**

Table 7 shows the difference in monthly average returns between green portfolios (high E rating group) and non-green portfolios (low E rating group) obtained by grouping by circulating market cap (quartile), book-to-market ratio (quartile), and E rating (trichotomy) during 2009-2020. After controlling for circulating market cap and book-to-market ratio, we obtain 16 groups. Intuitively, 11 groups show negative values, suggesting a positive carbon risk premium during 2009-2020, i.e., low E rating portfolios have higher stock returns. However, the t-value for the 16 time series is 0.42, which is not significant.

#### **Table 7 Full Sample Monthly Average Return Differences Between Green and Non-Green Portfolios (%)**

Table 8 adds the green factor GMNG (trichotomy) to the three-factor model, with columns (1)-(6) showing the same order as Table 6. The green factor GMNG is significant in all regressions, indicating it has significant power to explain cross-sectional differences in China's A-share market stock returns. Notably, in green portfolio regression column (1) and green individual stock regression column (4), the green factor GMNG coefficient is significantly positive; in non-green portfolio regression column (2) and non-green individual stock

regression column (5), the green factor GMNG coefficient is significantly negative. This shows that green and non-green stocks have different exposures to the green factor GMNG, with green stocks having positive factor exposure and non-green stocks having negative exposure. When the green factor GMNG's expected return is positive, it indicates green stocks have higher expected returns than non-green stocks, showing a green incentive; when negative, it shows the opposite, indicating a carbon risk premium. Due to the positive and negative differences in green and non-green stocks' exposures to the green factor GMNG, the significance of the green factor coefficient in column (6) full sample regression is weaker than in columns (4) and (5) group regression results.

#### **Table 8 Four-Factor Model Regression Results**

*Note:* , , \* indicate significance at 1%, 5%, and 10% levels respectively. All regressions use clustered robust standard errors.\*

#### **Determination of Carbon Risk Premium Sign**

Tables 7 and 8 show that China's A-share market's exposure to the green factor GMNG is significantly non-zero during 2009-2020, but the sign of the green factor GMNG is not significant. This section further studies the sign of China's green factor GMNG.

First, we use OLS regression to test the carbon premium sign in the A-share market over the full sample period, incorporating quarterly stock returns, E ratings, and control variables from 2009-2020 into regression analysis. Results are shown in Table 9 .

#### **Table 9 OLS Regression Results Under Different Fixed Effects for Full Sample**

In Table 9, columns (1)-(4) show that E rating coefficients are all insignificant, indicating that China's A-share market does not have a significant carbon premium overall during 2009-2020. Column (1) without any fixed effects shows an insignificant green incentive in the A-share market; columns (2) and (3) control for CSRC industry sector and major industry fixed effects respectively, with E rating coefficients smaller than those without fixed effects, suggesting fixed effects absorb part of the negative carbon premium. Column (4) controls for individual fixed effects, showing negative E rating regression results, indicating an insignificant negative carbon premium in the A-share market during 2013-2020. The substantial changes in E rating coefficients from columns (1)-(4) demonstrate that fixed effects can control for some endogeneity issues.

The full sample regression for 2009-2020 does not show a significant carbon risk premium or green incentive in the A-share market, but this does not mean the A-share market never had a carbon risk premium or green incentive at any time. Han Guowen and Fan Chengheng (2021) found that China's stock market experienced a shift from green incentive to carbon risk premium during 2013-2014, and such shifts may have occurred at other times. To observe changes

in the A-share market's green incentive, we conduct rolling regressions with a two-year window to obtain negative carbon premiums and their p-values, as shown in Figure 1 [Figure 1: see original paper].

The solid line represents the regression coefficient of E rating, i.e., the estimated negative carbon premium. The coefficient is negative during 2013-2015, indicating a positive carbon risk premium, consistent with Han Guowen and Fan Chengheng (2021). During 2016-2019, the market's carbon risk premium shifted to show a green incentive, with p-values for 2016, 2018, and 2019 all below 0.2, at relatively low levels. In summary, Figure 1 suggests that the A-share market's carbon risk premium shifted again during 2015-2016, with green incentive dominating after 2016, thus overall showing an insignificant carbon premium.

### **Figure 1 Rolling Regression Results of Carbon Risk Premium and P-values**

Based on Figure 1, dividing the sample period into 2013-2015 and 2016-2020 yields the return difference table between high and low E rating portfolios constructed according to circulating market cap, book-to-market ratio, and E rating, as shown in Table 10. The table shows that during 2013-2015, 12 of 16 monthly return differences are negative, intuitively suggesting a possible positive carbon risk premium in China's A-share market during this period, but the t-value is only -0.65. During 2016-2020, 11 of 16 monthly return differences are positive, intuitively suggesting a possible negative carbon risk premium in China's A-share market during this period, with the t-value reaching 2.09, significant at the 5% level.

### **Table 10 Monthly Average Return Differences Between Green and Non-Green Portfolios by Sub-period (%)**

Table 11 shows grouped OLS regression results after dividing the sample period. Column (1) shows results for sample stocks during 2013-2015, and column (2) for 2016-2020. Market risk Beta coefficients are significantly positive in both, book-to-market ratio coefficients are significantly positive, and log circulating market capitalization results are significantly negative, consistent with the Fama-French three-factor model. In column (1), the E rating coefficient is significantly negative at the 5% level, with a value of -0.556, indicating that each one-level increase in E rating reduces quarterly returns by 0.5% on average, with low E rating stocks having higher returns, showing a significant positive carbon risk premium. In column (2), the E rating coefficient is significantly positive at the 5% level, with a value of 0.283, indicating that high E rating stocks can achieve higher returns, and the A-share market has a significant negative carbon premium.

### **Table 11 OLS Regression Results by Sub-period**

*Note:* , , \* indicate significance at 1%, 5%, and 10% levels respectively. All regressions use clustered robust standard errors.\*

## Carbon Risk Premium and “Green Finance” Baidu Index

We have established that China’s A-share market experienced a shift from carbon risk premium to green incentive during 2015-2016, during which investors’ understanding of carbon risk changed. In April 2015, the Central Committee and the State Council issued the “Opinions on Accelerating the Construction of Ecological Civilization,” marking the beginning of China’s green finance development. On September 21, 2015, the Central Committee and the State Council printed and distributed the “Overall Plan for Ecological Civilization System Reform,” which first clarified the top-level design of China’s green financial system (Ma Jun, 2016).

The Baidu hot word index for the keyword “green finance” is shown in Figure 2 [Figure 2: see original paper]. Before 2013, the search frequency for “green finance” remained basically unchanged at a low level. During 2014-2015, search frequency volatility increased with a slight upward trend, rising significantly after September 2015. On August 31, 2016, the People’s Bank of China and six other ministries jointly issued the “Guiding Opinions on Establishing the Green Financial System,” clarifying the policy framework for green finance development. During the same period, the Baidu index for “green finance” rose substantially and remained at a high level. Clear central government policies may have provided investors with more information for reasonable carbon risk expectations, which could be one reason for the sign change in the A-share market’s carbon risk premium, though further quantitative research is needed.

### Figure 2 Time Series of Green Factor GMNG Cumulative Returns and “Green Finance” Baidu Index

## Robustness Tests

This section conducts robustness tests by changing the green factor GMNG (dichotomy) portfolio grouping method, using total market capitalization weighting to calculate portfolio returns, and changing the financial data matching method in OLS regression. The three robustness test results are basically consistent, indicating reliable and valid empirical conclusions.

## Dichotomy Construction of Green Factor

Dividing the sample period into 2013-2015 and 2016-2020, we use the dichotomy method to construct the green factor, combined with grouping by circulating market capitalization (quartile) and book-to-market ratio (quartile). Taking intersections and using the monthly average return of green stocks minus non-green stocks yields Table 12 . As shown, from the full sample perspective, most monthly return differences are negative, with non-green enterprises having higher returns, suggesting a possible positive carbon risk premium. During 2013-2015, most monthly return differences are negative, while during 2016-2020, most are positive. In summary, the basic conclusion about the carbon premium sign from mimicking portfolio construction remains unchanged.

**Table 12 Monthly Average Return Differences Between Dichotomy Green and Non-Green Portfolios (%)****Total Market Capitalization Weighting for Green Factor**

Using total market capitalization weighting to reconstruct portfolios and various factors, the matrix of monthly average return differences between green and non-green companies from portfolios based on green factor (trichotomy), circulating market capitalization (quartile), and book-to-market ratio (quartile) is shown in Table 13, with conclusions remaining unchanged.

**Table 13 Monthly Average Return Differences Between Total Market Cap-Weighted Green and Non-Green Portfolios (%)**

Four-factor model regression results are shown in Table 14. Three-factor model results are basically consistent with circulating market capitalization weighting, with the only exception being that book-to-market ratio is no longer significant when regressing green individual stocks over the full sample period, which is omitted due to space limitations. Comparing Table 14 with Table 8, main conclusions remain unchanged.

**Table 14 Four-Factor Model Regression Results with Total Market Cap Weighting**

*Note:* , , \* indicate significance at 1%, 5%, and 10% levels respectively. All regressions use clustered robust standard errors.\*

**Changing Financial Data Matching Method in OLS Regression**

The financial data used in the OLS regression of individual stock quarterly returns above are matched according to the most recent available principle, which may cause some selection bias. Therefore, Table 15 shows regression results using matching method 2 from Table 2. Due to space limitations, only regression results controlling for individual and time fixed effects are shown, with main conclusions remaining consistent.

**Table 15 OLS Regression Results After Changing Financial Matching Method**

*Note:* , , \* indicate significance at 1%, 5%, and 10% levels respectively. All regressions use clustered robust standard errors.\*

**Conclusions and Recommendations**

Since 2015, to transform from quantitative to high-quality economic development, China has officially begun constructing a green financial system. As the most important equity financing market for listed companies in China, how investors in the A-share market assess carbon risk faced by green and non-green enterprises deserves our attention.

Against this background, this paper uses China Securities Index E rating as a proxy for listed companies' carbon risk exposure and analyzes the existence and sign of carbon risk premium for 4,412 listed companies in the A-share market from 2009-2020. Empirical results are as follows:

1. The green factor has significant pricing power over the full sample period. The green factor added to the Fama-French three-factor model has significant pricing power throughout the sample period.
2. The sign of carbon risk premium is difficult to determine over the full sample period. Mimicking portfolio results show that during 2009-2020, 11 of 16 long-short portfolios have negative monthly average returns, intuitively indicating an overall positive carbon risk premium, i.e., non-green companies have excess returns. However, in OLS regression with more control variables, E rating regression results are insignificant.
3. China's A-share market experienced a shift from positive to negative carbon risk premium during 2015-2016. Rolling OLS regression and sub-period observation of mimicking portfolio returns show that during 2013-2015, China's A-share market had a significant positive carbon risk premium, while during 2016-2020, it had a significant negative carbon risk premium.
4. The sign shift of carbon risk premium is highly correlated with green financial system policy releases. Based on the time series chart of green factor cumulative returns and Baidu index for "green finance" keyword, we find high correlation among the turning point of green factor returns, "green finance" search frequency, and green finance policy releases, though further research is needed.

This study has both theoretical and practical significance. Theoretically, it enriches research on green factor pricing power in developing country capital markets, showing that carbon risk premium signs can shift with market development and policy implementation. Additionally, it offers insights for green financial system construction. As the green financial system develops, the sign of carbon risk premium may shift again.

## References

- [1] Ma Jun. Development and Prospects of Green Finance in China[J]. *Comparative Economic & Social Systems*, 2016(06):25-32.
- [2] Hoffmann V H, Busch T. Corporate carbon performance indicators: Carbon intensity, dependency, exposure, and risk[J]. *Journal of Industrial Ecology*, 2008, 12(4): 505-520.
- [3] Fama E F, French K R. Common risk factors in the returns on stocks and bonds[J]. *Journal of financial economics*, 1993, 33(1): 3-56.
- [4] Han Liyan, Cai Lixin, Yin Libo. Green Incentive in China's Securities Market: A Four-Factor Model[J]. *Journal of Financial Research*, 2017, 439(1): 145-161.
- [5] Atan R, Alam M M, Said J, et al. The impacts of environmental, social,

and governance factors on firm performance: Panel study of Malaysian companies[J]. Management of Environmental Quality: An International Journal, 2018.

[6] Liu Yong, Bai Xiaoying. Green Incentive in China's Stock Market: A Sustainable Development Perspective[J]. Economic Management, 2020, 42(01):155-173.

[7] Zhou Fangzhao, Pan Wanying, Fu Hui. ESG Responsibility Performance and Institutional Investors' Holding Preferences[J]. Scientific Decision Making, 2020(11):15-41.

[8] Oestreich A M, Tsiakas I. Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme[J]. Journal of Banking & Finance, 2015, 58: 294-308.

[9] Bolton P, Kacperczyk M. Do investors care about carbon risk?[J]. Journal of financial economics, 2021, 142(2): 517-549.

[10] Luo D. ESG, liquidity, and stock returns[J]. Journal of International Financial Markets, Institutions and Money, 2022, 78: 101526.

[11] Wei Ping, Shu Hao. Does China's Capital Market Recognize Green Investment?—Analysis Based on Green Funds[J]. Journal of Finance and Economics, 2018, 44(05):23-35.

[12] Li Jin. Research on ESG Risk Premium and Additional Returns in China's A-Share Market[J]. Securities Market Herald, 2021(06):24-33.

[13] Qiu Muyuan, Yin Hong. Corporate ESG Performance and Financing Costs under Ecological Civilization Construction[J]. The Journal of Quantitative & Technical Economics, 2019, 36(03):108-123.

[14] Han Guowen, Fan Chengheng. Corporate Carbon Emissions and Stock Returns—Green Incentive or Carbon Risk Premium[J]. Financial Economics Research, 2021, 36(04):78-93.

[15] Pedersen L H, Fitzgibbons S, Pomorski L. Responsible investing: The ESG-efficient frontier[J]. Journal of Financial Economics, 2021, 142(2): 572-597.

[16] Lash J, Wellington F. Competitive advantage on a warming planet[J]. Harvard Business Review, 2007, 85(3): 94-102, 143.

[17] Zhang Xueyong, Liu Qian. Research Progress on Carbon Risk Impact on Financial Markets[J]. Economic Perspectives, 2022(06):115-130.

[18] Cao Qun, Xu Qian. Research on Financial “Environmental, Social and Governance” (ESG) System Construction[J]. Financial Regulation Research, 2019(04):95-111.

[19] Wang Kai, Zhang Zhiwei. Current Status, Comparison and Prospects of ESG Ratings at Home and Abroad[J]. Finance and Accounting Monthly, 2022(02):137-143.

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