

## Article

# Navigating the Effect of Environmental Uncertainty on Carbon Emission: Evidence from Chinese Non-Financial Enterprises

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## Abstract

Environmental uncertainty (EU) has become one of the key determinants influencing corporate decision-making, yet the existing literature has not sufficiently explored its effects. Based on the data from Chinese non-financial public companies during the period from 2010 to 2023, we examine the impact of EU on carbon emission. The empirical results show that EU has a significant negative impact on corporate carbon emission. Specifically, a one-unit increase in EU leads to approximately a 9.13 percent decline in carbon emission. Furthermore, we find that EU increases firms' financing constraints, thereby reducing capacity-utilization and carbon emission. Meanwhile, EU can spur innovation, resulting in active decarbonization. Finally, the finding is more pronounced in non-state-owned enterprises (N-SOEs). The above findings shed light on promoting carbon reduction for policymakers and corporate operators.

**Keywords:** environmental uncertainty; corporate carbon emission; financing constraints; innovation

## 1. Introduction

Presently, the environmental problems such as climate change, pollution and ecological degradation are intensifying, causing severe economic losses worldwide [1]. Meanwhile, a growing number of investors, consumers, and governments are recognizing the importance of protecting the environment [2]. These issues highlight the necessity of reducing carbon emission. As the primary microeconomic entities, enterprises play a critical role in fulfilling their carbon reduction responsibilities and driving the green transition.

The determinants of carbon emission have been hotspots, and yielded substantial findings, which involve the city-level perspective [3–5], and the firm-level perspective [6–8], with a consensus that business environmental factors affect corporate decision-making and subsequent emissions. Prior studies have identified significant impacts of internal and external factors, including regulation, financial policy, digital transformation, and corporate characteristics [9,10]. However, these studies leave a critical gap in understanding how the volatility of the business environment—termed environmental uncertainty (EU)—influences corporate carbon emission.

EU, defined as the degree of unpredictable change in a firm's operating environment stemming from both macro-level (e.g., policy shifts, business cycles) and micro-level (e.g., operational volatility) [11]. A growing body of studies have examined the consequences of EU, such as corporate investments [12], innovation [13–15], environmental



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performance [16,17] and ESG performance [2,18]. To the best of our knowledge, research on the relationship between EU and carbon emission is insufficient.

On the one hand, most studies analyze EU through the lens of specific policy uncertainty, such as economic, climate, or trade policy [19,20], utilizing macro-level indicators like Economic Policy Uncertainty (EPU) or Climate Policy Uncertainty (CPU) indices constructed from news text data [21]. However, these city-level indices suffer from a critical limitation: they treat all enterprises as homogenous receptors of policy shocks, neglecting the heterogeneous responses and resilience of individual enterprises. On the other hand, the empirical results are mixed. For example, most studies conclude that EPU has a positive association with carbon emission [22–24], while carbon emission can be reduced in face of CPU [25–27].

China offers a good research sample for exploring how EU affects corporate carbon emission. Firstly, as the world's largest carbon emitter, China is requested to balance economic development and environmental protection. Therefore, carbon peaking and carbon neutrality goals are put forward to reduce carbon emission, further making a substantive contribution to enhancing global climate resilience. Secondly, China is undergoing economic transformation and high-quality economic development, as well as trade frictions, increasing the uncertainty of business environment, and further having an impact on corporate carbon emission.

To fill the above research gaps, we investigate the relationship between micro-level EU and carbon emission using the data of Chinese non-financial companies listed on the Shanghai and Shenzhen stock markets from 2010 to 2023. Drawing on the option theory and asymmetric information theory, we examine the possible channels through which EU affects corporate carbon emission. The main findings are as follows: Firstly, EU has a significant negative association with carbon emission. Secondly, EU tightens financing constraints and forces firms to reduce capacity-utilization, ultimately reducing emission. Additionally, EU increases the option value of innovative investments, further leading to emission reduction. Finally, the heterogeneity results show that the negative impact of EU on carbon emission is more pronounced in N-SOEs.

Twofold contributions are provided to the literature in the following ways. Firstly, we advance the understanding of the relationship between EU and carbon emission by shifting the analytical lens from policy uncertainty to firm-level operational volatility. Unlike previous research that employs macro-level indices and neglects firm heterogeneity, we use micro-level EU to identify the actual transmission channel through which uncertainty materializes in emission outcomes. Secondly, our study sheds light on the mechanisms through which EU influences corporate carbon emission. While prior studies largely focus on proactive channels through which uncertainty reduces emissions, we uncover a passive chain mechanism whereby EU tightens financing constraints, which in turn lowers capacity-utilization and ultimately reduces carbon emissions.

## 2. Theoretical Mechanisms and Hypotheses

The theoretical framework of this study is grounded in two complementary strands of economic theory—information asymmetry theory and option theory—which jointly predict that firm-level EU affects corporate carbon emission through dual channels. The first channel suggests that EU widens the information gap between firms and external capital providers, tightening financing constraints and forcing firms to curtail capacity-utilization—a passive channel that mechanically reduces emission. The second channel posits that EU increases the option value of innovative investments, actively reducing emission.

### 2.1. Passive Decarbonization Effect

Increased EU may exacerbate the enterprise's financing constraints, further leading to lower capacity-utilization. This passive decarbonization effect operates primarily in the following pathways.

Firstly, the positive relationship between EU and financing constraints is explained by information asymmetry and capital costs, especially for small- and medium-sized, high-energy-consuming enterprises [28]. Specifically, EU widens the information gap between enterprises and external capital providers, making it difficult for external investors to accurately assess enterprises' future profitability and debt repayment risks, which leads to a tightening of credit supply [29]. Additionally, higher capital premiums for investors are required to compensate for the increased risks resulting from EU, such as operational risks and financial risks [30], thereby increasing the capital costs of external financing.

Secondly, financing constraints further reduce capacity-utilization rates. In detail, financing constraints directly limits enterprises' ability for capital investment, preventing them from timely upgrading equipment or optimizing production capacity, which leads to a decline in effective capacity and makes it difficult for actual output to reach its potential level [31]. Financing constraints also reduce capacity-utilization by influencing enterprises' short-term operational decisions. Research indicates that enterprises facing financing constraints are unable to quickly build inventories when faced with favorable demand shocks, and cost constraints force enterprises to reduce actual output to cope with liquidity pressures [32].

Based on the above analysis, we propose the following hypothesis:

**H1.** *EU has a significant negative association with corporate carbon emission.*

**H2.** *EU passively reduces corporate carbon emission by strengthening financing constraints.*

### 2.2. Active Decarbonization Effect

Increased EU may improve the enterprise's innovation, further resulting in lower carbon emission. The active decarbonization effect can be explained from the following aspects.

Firstly, although innovation is a high-risk and long-term investment, active innovation enhances enterprise's production capacity, total factor productivity and competitive edge, contributing to potential profitability. Thus, the innovation decisions depend on the trade-off between innovation input costs and corresponding output benefits. Different from real options theory, excess profit opportunities increase the value of innovation options in face of high EU; enterprises thus tend to increase R&D innovation [33].

Secondly, high EU causes operational pressures, such as market fluctuations, exacerbating market competition and survival risks. Therefore, increasing R&D innovation is the best choice to cope with the universal crisis, providing opportunities for enterprises to expand their market position [34,35]. Specifically, enterprises are forced to enhance innovation outputs to gain competitive advantages. For example, intensifying trade policy uncertainties lead to supply interruptions for certain imported goods, compelling Chinese enterprises to reorient their R&D priorities, and replacing previously relied-upon overseas products with domestic alternatives [36].

Finally, with the strengthening of global environmental regulation and the improvement of social environmental awareness, low-carbon development has become an important part of corporate legitimacy. Therefore, corporate innovation actively contributes to emission reduction and revenue streams amidst EU [37].

Based on the above analysis, we then propose the following hypothesis:

**H3.** *EU actively reduces corporate carbon emission by improving corporate innovation.*

### 3. Data and Methodology

#### 3.1. Variables

The dependent variable is corporate carbon emission (CCE). According to the definition of database, the specific formula is as follows (this measurement method is sourced from the CSMAR database):

$$CCE_{it} = SCC_{ijt} \times CF \times weight_{ijt} \quad (1)$$

where  $SCC_{ijt}$  refers to the total standard coal consumption in the national economic sector  $j$  where the listed company  $i$  operates in year  $t$ .  $CF$  is carbon dioxide conversion factor; according to Xiamen Energy Conservation Center, the conversion factor for 1 metric ton of standard coal is 2.493.  $weight_{ijt}$  is the ratio of operating costs for listed company  $i$  to the operating costs of national economic sector  $j$  in which listed company  $i$  operates in year  $t$ .

The core independent variable is environmental uncertainty (EU) index, which results in a fluctuation in corporate sales revenues; (we use the industry-adjusted standard deviation of the residuals of sales revenue over five consecutive years to measure environmental uncertainty. The formula is as follows:

$$Sale = \alpha + \beta Year + \epsilon \quad (2)$$

where  $Sale$  is sales revenue, and  $Year$  is an annual variable. For the current year,  $Year = 5$ ; for the first previous year,  $Year = 4$ ; and so on, with  $Year = 1$  for the fourth previous year. The residual  $\epsilon$  of the equation represents the abnormal sales revenue of the firm over the past five years. The firm's environmental uncertainty is obtained by dividing the standard deviation of the abnormal sales revenue over the past five years by the average sales revenue over the same period. To eliminate industry effects, the firm-level environmental uncertainty is divided by the industry-level environmental uncertainty, which is defined as the median value of all firms in the same industry and year.); thus, it is measured by the standard deviation of corporate sales revenues following the method of [38].

In addition, we select several control variables to minimize the estimation bias, including firm size ( $Size$ ), firm age ( $Age$ ), the ratio of fixed capital ( $Fix$ ), the ratio of assets to liability ( $ALR$ ), book-to-market ratio ( $BM$ ), corporate growth ( $Growth$ ), shareholding ratio of the top ten shareholders ( $Top$ ), and separation rate of two rights ( $Sep$ ). The definition of the controls is shown in Table 1.

**Table 1.** The definition of variables.

| Variable      | Description                                                                             |
|---------------|-----------------------------------------------------------------------------------------|
| <i>CCE</i>    | The natural logarithm of corporate carbon emission plus one                             |
| <i>EU</i>     | Measured by standard deviation of corporate sales revenues                              |
| <i>Size</i>   | The natural logarithm of total assets                                                   |
| <i>Age</i>    | The natural logarithm of the total number of years since the firm first listed plus one |
| <i>Fix</i>    | Ratio of fixed assets to total assets                                                   |
| <i>ALR</i>    | The ratio of total liabilities to total assets                                          |
| <i>BM</i>     | The ratio of total assets to market value                                               |
| <i>Growth</i> | Growth rate of total assets                                                             |
| <i>TOP</i>    | The proportion of shares held by the top ten shareholders to all shareholders           |
| <i>Sep</i>    | The difference between control rights (%) and ownership rights (%)                      |

#### 3.2. Data

Our data is sourced from China Stock Market and Accounting Research (CSMAR) database of non-financial firms listed on the Shanghai and Shenzhen A-share markets,

covering the period from 2010 to 2023. We further exclude companies listed for less than one year, companies with a book-to-market ratio below zero, and companies with missing variables, yielding a total of 18,881 observations. In addition, all variables are tailed by 1–99% in regressions, and the summary statistics are listed in Table 2.

**Table 2.** The summary statistics of variables.

| Variable      | N      | Mean  | SD    | Min    | p50    | Max   |
|---------------|--------|-------|-------|--------|--------|-------|
| <i>CCE</i>    | 18,881 | 11.21 | 1.970 | 7.310  | 10.99  | 16.48 |
| <i>EU</i>     | 18,881 | 1.260 | 1.030 | 0.160  | 0.980  | 6.120 |
| <i>Size</i>   | 18,881 | 22.42 | 1.230 | 20.07  | 22.25  | 26.10 |
| <i>Age</i>    | 18,881 | 2.400 | 0.560 | 1.390  | 2.400  | 3.370 |
| <i>Fix</i>    | 18,881 | 0.240 | 0.140 | 0.0200 | 0.210  | 0.670 |
| <i>ALR</i>    | 18,881 | 0.430 | 0.190 | 0.0700 | 0.430  | 0.880 |
| <i>BM</i>     | 18,881 | 0.330 | 0.150 | 0.0500 | 0.310  | 0.780 |
| <i>Growth</i> | 18,881 | 0.110 | 0.210 | −0.280 | 0.0700 | 1.120 |
| <i>TOP</i>    | 18,881 | 54.98 | 14.50 | 22.67  | 54.81  | 89.15 |
| <i>Sep</i>    | 18,881 | 4.970 | 7.530 | 0      | 0      | 28.60 |

From Table 2, the mean value and standard deviation of carbon emission are 11.21 and 1.97, respectively, indicating that significant variation in carbon emission among the sample. Additionally, the median value ( $p50 = 10.99$ ) is approximately equal to the mean value, suggesting a non-skewed distribution. Additionally, the mean value of *EU* is 1.26, with a standard deviation of 1.03, showing that the sample exhibits significant fluctuations. Finally, the analysis of control variables is similar to the aforementioned variables and will therefore not be repeated here.

### 3.3. Models

To test our hypotheses, we first construct the two-way fixed regression model to examine the effect of *EPU* on corporate carbon emission:

$$CCE_{i,j,t+1} = \beta_0 + \beta_1 EU_{i,j,t} + \beta Controls + p_j + u_t + \varepsilon_{i,j,t} \quad (3)$$

where  $CCE_{i,j,t+1}$  is total carbon emission of enterprise  $i$  in industry  $j$  in year  $t + 1$ .  $EU_{i,j,t}$  is the uncertainty index of environmental for enterprise  $i$  in industry  $j$  in year  $t$ . Controls are a series of firm-level control variables that may affect carbon emission.  $p_j$  and  $u_t$  represent the industry-fixed effect and time-fixed effect, respectively.  $\varepsilon_{i,j,t}$  is the random term.  $\beta_1$  is the estimated parameter in this study, and its sign determines the direction of the effect of *EU* on carbon emission.

Furthermore, to verify the mechanism through which *EU* affects corporate carbon emission, a two-step regression model is employed:

$$Me_{i,j,t} = \alpha_0 + \alpha_1 EU_{i,j,t} + \alpha Controls + p_j + u_t + \varepsilon_{i,j,t} \quad (4)$$

$$CCE_{i,j,t+1} = \lambda_0 + \lambda_1 EU_{i,j,t} + \lambda_2 Med_{i,j,t} + \lambda Controls + p_j + u_t + \varepsilon_{i,j,t} \quad (5)$$

where  $Me_{i,t}$  is mechanism variables.

## 4. Results

### 4.1. Baseline Results

The main results for *EU* coefficients are shown in Table 3. Specifically, columns (1) and (3) are the results without controlling for fixed effect, while column (3) adds control variables compared to column (1). In contrast, column (2) reports the results for considering

fixed effect and the results which incorporate control variables are further shown in column (4). Overall, all of the columns indicate that the coefficients of EU are significant and negative; especially the coefficient ( $-0.0957$ ) in column (4) indicates a one-unit increase in EU leads to approximately a 9.13 (the dependent variable is in natural logarithm while the independent variable EU is in levels, the coefficient  $\beta$  can be interpreted as follows: a one-unit change in EU leads to a  $(e^{\beta} - 1) \times 100\%$  change in carbon emission) percent decline in carbon emission, and thus H1 is supported. Moreover, our finding is consistent with some studies on CPU [25–27], but contrasts with most studies on EPU, which report a positive relationship between EPU and carbon emission [22–24,39]. We attribute this discrepancy to two key differences: macro-level EPU indices capture anticipated policy signals, whereas our micro-level EU captures realized operational shocks; studies finding positive effects typically rely on cross-country data with heterogeneous institutional contexts, whereas our China-focused analysis benefits from a unified regulatory environment shaped by the “dual carbon” goals.

**Table 3.** The main results of baseline model.

| Variables       | (1)<br>CCE               | (2)<br>CCE                | (3)<br>CCE                 | (4)<br>CCE                 |
|-----------------|--------------------------|---------------------------|----------------------------|----------------------------|
| <i>EU</i>       | −0.1650 ***<br>(−5.0168) | −0.1265 ***<br>(−4.4811)  | −0.1118 ***<br>(−7.0195)   | −0.0957 ***<br>(−6.7104)   |
| <i>Size</i>     |                          |                           | 0.9672 ***<br>(19.7745)    | 0.9517 ***<br>(44.2104)    |
| <i>Age</i>      |                          |                           | 0.2820 ***<br>(4.1286)     | 0.1610 ***<br>(6.2892)     |
| <i>Fix</i>      |                          |                           | 3.5390 ***<br>(7.1469)     | 0.5023 ***<br>(3.7370)     |
| <i>ALR</i>      |                          |                           | 1.2793 ***<br>(3.4809)     | 0.8494 ***<br>(6.3552)     |
| <i>BM</i>       |                          |                           | 1.1493 ***<br>(3.9571)     | 0.1458<br>(1.1500)         |
| <i>Growth</i>   |                          |                           | 0.4445 ***<br>(2.7735)     | 0.1630 ***<br>(3.4678)     |
| <i>Top</i>      |                          |                           | 0.0067<br>(1.6065)         | 0.0059 ***<br>(10.0442)    |
| <i>Sep</i>      |                          |                           | 0.0032<br>(0.7991)         | 0.0017<br>(1.0824)         |
| <i>Constant</i> | 11.5043 ***<br>(35.6749) | 11.4566 ***<br>(328.0085) | −13.1332 ***<br>(−11.1442) | −11.1861 ***<br>(−25.2908) |
| <i>Industry</i> | No                       | Yes                       | No                         | Yes                        |
| <i>Year</i>     | No                       | Yes                       | No                         | Yes                        |
| Observations    | 15,511                   | 15,484                    | 15,511                     | 15,484                     |
| R-squared       | 0.0072                   | 0.5585                    | 0.6521                     | 0.8998                     |

Note: Robust t-statistics are in parentheses, and \*\*\* denotes significance at the 1% levels, respectively. The inconsistency between the sample observations and the descriptive statistics is due to the loss of first-period observations from one-period lagging of certain variables.

All of the coefficients of control variables are significant and positive. For example, firm’s scale has a positive association with carbon emission, which is consistent with [40]. Firm age has a significantly positive effect on carbon emission, indicating that older firms bring higher carbon emission. This finding is explained by organizational inertia [41].

Firms with higher fixed assets are primarily heavy polluters [42], and thus the coefficient of Fix is positive. Firms with high debt-to-asset ratios and profitability typically exhibit low levels of green innovation [43], thereby increasing carbon emission. The coefficient of Top is positive at the 1% significance level, which is consistent with the finding of [44].

#### 4.2. Robustness Checks

Additional robustness and endogeneity checks are conducted to improve the robustness of baseline results, and the results are shown in Table 4.

**Table 4.** The robustness and endogeneity checks.

| Variables       | (1)<br>CCE                 | (2)<br>CCE                 | (3)<br>CCE                 | (4)<br>CCE                 | (5)<br>CCE                 | (6)<br>EU                | CCE                      |
|-----------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|--------------------------|--------------------------|
| <i>EU_U</i>     | −0.8857 ***<br>(−5.9900)   |                            |                            |                            |                            |                          |                          |
| <i>EU</i>       |                            | −0.0958 ***<br>(−6.7032)   | −0.0950 ***<br>(−6.6998)   | −0.0874 ***<br>(−6.8194)   |                            |                          | −0.1415 ***<br>(−6.2909) |
| <i>Vol</i>      |                            |                            |                            |                            | −0.5788 ***<br>(−5.3476)   |                          |                          |
| <i>L.EU</i>     |                            |                            |                            |                            |                            | 0.6770 ***<br>(48.9223)  |                          |
| <i>Size</i>     | 0.9525 ***<br>(44.6404)    | 0.9521 ***<br>(44.1085)    | 0.9499 ***<br>(43.7877)    | 0.9500 ***<br>(40.3350)    | 0.9472 ***<br>(43.5952)    | −0.0489 ***<br>(−7.4604) | 0.9442 ***<br>(41.2736)  |
| <i>Age</i>      | 0.1614 ***<br>(6.3101)     | 0.1651 ***<br>(6.6900)     | 0.1623 ***<br>(6.0586)     | 0.1643 ***<br>(5.1189)     | 0.1479 ***<br>(5.6201)     | 0.0180<br>(1.1296)       | 0.1891 ***<br>(6.3988)   |
| <i>Fix</i>      | 0.5054 ***<br>(3.7256)     | 0.5079 ***<br>(3.8376)     | 0.5079 ***<br>(3.4890)     | 0.4170 ***<br>(2.9041)     | 0.5000 ***<br>(3.6035)     | −0.0195<br>(−0.3801)     | 0.4980 ***<br>(3.5911)   |
| <i>ALR</i>      | 0.8432 ***<br>(6.2987)     | 0.8502 ***<br>(6.3803)     | 0.8146 ***<br>(5.9584)     | 0.8494 ***<br>(5.4920)     | 0.8249 ***<br>(6.1978)     | 0.1617 ***<br>(4.0317)   | 0.8281 ***<br>(5.9272)   |
| <i>BM</i>       | 0.1422<br>(1.1318)         | 0.1438<br>(1.1265)         | 0.1244<br>(0.9749)         | 0.1667<br>(1.3240)         | 0.0629<br>(0.4712)         | 0.0435<br>(0.7418)       | 0.1375<br>(0.9779)       |
| <i>Growth</i>   | 0.1621 ***<br>(3.4604)     | 0.1629 ***<br>(3.4642)     | 0.1806 ***<br>(3.5761)     | 0.0338<br>(0.7302)         | 0.1198 ***<br>(2.8517)     | 0.4384 ***<br>(9.8224)   | 0.2155 ***<br>(4.3821)   |
| <i>Top</i>      | 0.0058 ***<br>(10.0750)    | 0.0060 ***<br>(10.3027)    | 0.0058 ***<br>(8.9314)     | 0.0056 ***<br>(9.4501)     | 0.0053 ***<br>(8.2867)     | 0.0008<br>(0.9590)       | 0.0063 ***<br>(9.1995)   |
| <i>Sep</i>      | 0.0018<br>(1.1144)         |                            | 0.0021<br>(1.3180)         | 0.0019<br>(1.2574)         | 0.0018<br>(1.1173)         | −0.0005<br>(−0.6271)     | 0.0015<br>(0.8965)       |
| <i>Constant</i> | −11.2037 ***<br>(−25.4509) | −11.2037 ***<br>(−25.3983) | −11.1258 ***<br>(−25.2901) | −11.1301 ***<br>(−22.4399) | −10.8040 ***<br>(−22.5336) |                          |                          |
| <i>Industry</i> | Yes                        | Yes                        | Yes                        | Yes                        | Yes                        | Yes                      | Yes                      |
| <i>Year</i>     | Yes                        | Yes                        | Yes                        | Yes                        | Yes                        | Yes                      | Yes                      |
| Observations    | 15,484                     | 15,484                     | 14,984                     | 10,184                     | 15,484                     | 12,638                   | 12,638                   |
| R-squared       | 0.8996                     | 0.8997                     | 0.9019                     | 0.8981                     | 0.8987                     |                          | 0.7782                   |

Note: Robust t-statistics are in parentheses, and \*\*\* denotes significance at the 1% levels, respectively. The inconsistency between the sample observations and the descriptive statistics is due to the loss of first-period observations from one-period lagging of certain variables.

Firstly, an alternative index (*EU\_U*) is adopted based on *EU*; in other words, new uncertainty index without industry-specific adjustments is employed, and the results are

reported in column (1). The coefficient of EU\_U is still significantly negative, indicating that the concluding is robust after changing the proxy variable of EU. We also construct a measure of stock-price-based uncertainty (Vol) by using monthly stock returns to reflect the annualized volatility of stock returns at the firm level, and the results are shown in column (5). The coefficient of Vol is  $-0.5788$ , and passes the significance test at the 1% level, indicating the baseline results are stable.

Notably, our focus is on exploring the impact of EU on carbon emission after controlling for other factors affecting carbon emission. In light of this, we further remove the control variable (Sep) to conduct the robustness check, and the re-estimated results are displayed in column (2). The coefficient is  $-0.0958$ , and passes the significance test, suggesting that the negative relationship between EU and carbon emission is insensitive to omitted observable variables.

Thirdly, significant differences exist between industrial and non-industrial enterprises in terms of the impact of EU on carbon emission. Especially, industrial enterprises may face stronger emission reduction demands in response to environmental risks. In line with this, we re-examine the relationship between EU and carbon emission using the sample of industrial sectors. The coefficient of EU in column (3) is negative at the 1% level, supporting the baseline results.

Fourthly, we excluded the observations in 2020 and 2021 from the sample to eliminate the biased impact of the COVID-19 epidemic on EU. The results are listed in column (4), where EU exhibits a significantly negative coefficient, indicating the baseline finding holds after changing the sample period.

Finally, we also conduct a two-stage model regression by using the one-period lag term EU (L.EU) as the instrumental variable to solve endogeneity. From the results of Column (6), we can observe that the significant coefficient in the first stage indicates that the instrumental variables and the endogenous variables are strongly correlated, and the coefficient of EU in second-stage is significantly negative, indicating the results are robust.

#### 4.3. Mechanism Tests

To further verify the possible mechanism through which EU affects corporate carbon emission, we conduct the model following Formulas (4) and (5), and the results are presented in Table 5.

**Table 5.** The possible channels.

| Variables | (1)<br>KZ                         | (2)<br>FAT                        | (3)<br>CCE                       | (4)<br>RD                        | (5)<br>CCE                        |
|-----------|-----------------------------------|-----------------------------------|----------------------------------|----------------------------------|-----------------------------------|
| KZ        |                                   | $-0.0738^{***}$<br>( $-12.8424$ ) | $0.0148^*$<br>( $1.8898$ )       |                                  |                                   |
| FAT       |                                   |                                   | $0.8101^{***}$<br>( $25.0056$ )  |                                  |                                   |
| RD        |                                   |                                   |                                  |                                  | $-0.0627^{***}$<br>( $-19.6250$ ) |
| EU        | $0.1435^{***}$<br>( $8.2074$ )    | $-0.0556^{***}$<br>( $-5.7529$ )  | $-0.0477^{***}$<br>( $-6.7669$ ) | $0.1527^{**}$<br>( $2.5014$ )    | $-0.0887^{***}$<br>( $-6.2314$ )  |
| Size      | $-0.4324^{***}$<br>( $-13.9081$ ) | $-0.0237^{**}$<br>( $-2.1149$ )   | $0.9523^{***}$<br>( $58.2571$ )  | $0.1710^*$<br>( $1.9253$ )       | $0.9610^{***}$<br>( $39.1503$ )   |
| Age       | $0.0665$<br>( $1.2765$ )          | $0.1610^{***}$<br>( $7.7096$ )    | $0.0347^{**}$<br>( $2.2137$ )    | $-1.0008^{***}$<br>( $-5.9456$ ) | $0.1074^{***}$<br>( $4.2079$ )    |

Table 5. Cont.

| Variables           | (1)<br>KZ                                     | (2)<br>FAT                | (3)<br>CCE                 | (4)<br>RD                                     | (5)<br>CCE                 |
|---------------------|-----------------------------------------------|---------------------------|----------------------------|-----------------------------------------------|----------------------------|
| <i>Fix</i>          | 0.6636 **<br>(2.5444)                         | −4.3818 ***<br>(−13.4994) | 4.0625 ***<br>(18.6261)    | −1.6587<br>(−1.5870)                          | 0.3898 **<br>(2.3309)      |
| <i>ALR</i>          | 7.5063 ***<br>(34.0046)                       | 0.7826 ***<br>(9.5914)    | 0.5461 ***<br>(4.3304)     | −4.4793 ***<br>(−6.6107)                      | 0.5730 ***<br>(4.7880)     |
| <i>BM</i>           | −1.5731 ***<br>(−5.8608)                      | −0.3910 ***<br>(−4.6234)  | 0.4142 ***<br>(3.4345)     | −3.7290 ***<br>(−4.9877)                      | −0.0779<br>(−0.6070)       |
| <i>Growth</i>       | −2.2375 ***<br>(−18.9636)                     | −0.2281 ***<br>(−7.7551)  | 0.2767 ***<br>(6.2652)     | −0.9867 **<br>(−2.1413)                       | 0.1347 ***<br>(2.9057)     |
| <i>Top</i>          | −0.0144 ***<br>(−6.6964)                      | 0.0043 ***<br>(9.4204)    | 0.0018 ***<br>(3.3153)     | −0.0197 ***<br>(−3.9655)                      | 0.0045 ***<br>(6.3309)     |
| <i>Sep</i>          | −0.0089 ***<br>(−3.1201)                      | 0.0018<br>(1.6025)        | −0.0002<br>(−0.1931)       | −0.0016<br>(−0.2574)                          | 0.0016<br>(0.9431)         |
| <i>Constant</i>     | 8.7327 ***<br>(13.1583)                       | 1.9269 ***<br>(9.8049)    | −12.3871 ***<br>(−34.6410) | 7.5772 ***<br>(6.2413)                        | −10.7215 ***<br>(−22.0762) |
| <i>Industry</i>     | Yes                                           | Yes                       | Yes                        | Yes                                           | Yes                        |
| <i>Year</i>         | Yes                                           | Yes                       | Yes                        | Yes                                           | Yes                        |
| Observations        | 18,854                                        | 18,854                    | 15,484                     | 18,114                                        | 14,940                     |
| R-squared           | 0.5617                                        | 0.6211                    | 0.9423                     | 0.3572                                        | 0.9086                     |
| Bootstrap test      | Coefficient = −0.009, Z = −9.927, $p = 0.000$ |                           |                            | Coefficient = −0.005, Z = −5.064, $p = 0.000$ |                            |
| Confidence interval | [−0.010, −0.007]                              |                           |                            | [−0.006, −0.003]                              |                            |

Note: Robust t-statistics are in parentheses, and \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. Specifically, the mechanism variables are measured in the following ways: The financing constraints (KZ) is defined as KZ index, referring to the method of [45]. Following [46], capacity-utilization (FAT) is measured using the ratio of operating revenue to fixed assets as a proxy variable. We further employ the ratio of R&D investment to operating revenue as a proxy variable for firm innovation (RD), as in [47]. All of the variables are also derived from CSMAR. Combining the basic data and mechanism variables into a new table has resulted in a further reduction in the data sample observations.

According to columns (1) to (3) of Table 5, the passive decarbonization channel is summarized as follows: The regression coefficient of EU on KZ in column (1) is significantly positive, indicating that the higher EU raises financing constraints. Second, an increase in financing constraints suppresses capacity-utilization, which is supported by the results of column (2). The coefficient of KZ on FAT is negative at the 1% significance level, while the direct coefficient of EU on FAT is also negative (−0.0556,  $p < 0.01$ ). This suggests that EU not only directly reduces capacity-utilization but also indirectly lowers FAT by increasing financing constraints. Furthermore, column (3) shows that capacity-utilization is significantly positively correlated with carbon emission (FAT coefficient of 0.8101,  $p < 0.01$ ), while the total effect of EU on CCE is negative (−0.0477,  $p < 0.01$ ), implying that EU generally reduces corporate carbon emission. We also conducted a bootstrap test with 1000 repetitions, and the results of the Sobel test statistics are reported in Table 5, indicating that this indirect effect is significant. Therefore, H2 is verified.

Similarly, columns (4) and (5) present the mechanism results of corporate innovation. We can see that the coefficient of EU in column (4) is positive at the 5% significance level, indicating that EU encourages innovation. The related Sobel test statistics are listed as follows: coefficient = −0.005, Z = −5.064,  $p = 0.000$ , indicating that the indirect effect is significant. Therefore, our empirical results support H3.

#### 4.4. Heterogeneity Analysis

##### 4.4.1. Firm Size Heterogeneity

The samples are divided into small-scale enterprises and large-scale enterprises to test the heterogeneous effects of firm scale on carbon emission, and the results are shown in columns (1) and (2) in Table 6, respectively. The estimated results show that EU has a negative impact on carbon emission for both large and small enterprises. Furthermore, in terms of the significance of the coefficient of variation between groups, the *p*-value for the test of differences in coefficients between large-scale and small-scale enterprises is 0.467, indicating that there is no significant difference in the impact of EU on carbon emission between large-scale and small-scale enterprises.

**Table 6.** The heterogeneous results.

| Variables                       | (1)<br>Small              | (2)<br>Large             | (3)<br>Heavily<br>_Polluting | (4)<br>Non-Heavily<br>_Polluting | (5)<br>SOEs                   | (6)<br>N-SOEs              |
|---------------------------------|---------------------------|--------------------------|------------------------------|----------------------------------|-------------------------------|----------------------------|
| <i>EU</i>                       | −0.1498 ***<br>(−7.5174)  | −0.1527 ***<br>(−8.5073) | −0.0971 ***<br>(−4.1709)     | −0.0951 ***<br>(−5.1076)         | −0.0716 ***<br>(−3.2258)      | −0.1022 ***<br>(−6.5346)   |
| <i>Size</i>                     |                           |                          | 0.9013 ***<br>(34.2158)      | 0.9954 ***<br>(50.4090)          | 0.9343 ***<br>(28.0934)       | 0.9646 ***<br>(45.2234)    |
| <i>Age</i>                      | 0.2323 ***<br>(6.8576)    | 0.5076 ***<br>(8.3000)   | 0.1610 ***<br>(3.3320)       | 0.1515 ***<br>(4.5229)           | 0.2591 ***<br>(5.8853)        | 0.0543 **<br>(2.6239)      |
| <i>Fix</i>                      | 0.2867 *<br>(1.7960)      | 0.5270 *<br>(1.9008)     | 0.6653 ***<br>(3.2347)       | 0.3836 ***<br>(5.2471)           | 0.3638 **<br>(2.5675)         | 0.6197 ***<br>(2.9485)     |
| <i>ALR</i>                      | 2.3159 ***<br>(19.2602)   | 2.6958 ***<br>(9.9441)   | 0.7535 ***<br>(3.4362)       | 0.8683 ***<br>(6.6090)           | 0.5929 **<br>(2.4190)         | 0.9623 ***<br>(7.8446)     |
| <i>BM</i>                       | 1.9465 ***<br>(15.0061)   | 1.1317 ***<br>(4.9358)   | 0.4000 **<br>(2.2395)        | −0.1476<br>(−1.3194)             | 0.3290<br>(1.3761)            | 0.0532<br>(0.3988)         |
| <i>Growth</i>                   | 0.5717 ***<br>(8.2427)    | 0.5540 ***<br>(4.8974)   | 0.1131<br>(1.1880)           | 0.1863 ***<br>(4.1448)           | 0.1969 **<br>(2.2506)         | 0.1591 ***<br>(3.3295)     |
| <i>Top</i>                      | 0.0050 ***<br>(3.5513)    | 0.0264 ***<br>(7.9076)   | 0.0060 ***<br>(6.3071)       | 0.0059 ***<br>(7.5935)           | 0.0055 ***<br>(2.8715)        | 0.0049 ***<br>(3.6869)     |
| <i>Sep</i>                      | 0.0062 ***<br>(2.9155)    | −0.0026<br>(−0.7675)     | 0.0007<br>(0.2945)           | 0.0021<br>(1.1971)               | 0.0011<br>(0.5439)            | 0.0030 *<br>(1.7755)       |
| <i>Constant</i>                 | 7.9644 ***<br>(55.5779)   | 7.8838 ***<br>(24.1154)  | −9.2905 ***<br>(−15.8650)    | −12.7651 ***<br>(−32.7425)       | −10.7005 ***<br>(−17.4885)    | −11.3720 ***<br>(−25.5798) |
| <i>Industry</i>                 | Yes                       | Yes                      | Yes                          | Yes                              | Yes                           | Yes                        |
| <i>Year</i>                     | Yes                       | Yes                      | Yes                          | Yes                              | Yes                           | Yes                        |
| Observations                    | 7717                      | 7745                     | 7149                         | 8331                             | 5680                          | 9791                       |
| R-squared                       | 0.7474                    | 0.7092                   | 0.8829                       | 0.8452                           | 0.9104                        | 0.8757                     |
| Fisher's<br>Permutation<br>test | 0.003 ( <i>p</i> = 0.467) |                          | 0.002 ( <i>p</i> = 0.416)    |                                  | 0.031 *** ( <i>p</i> = 0.009) |                            |

Note: Firm size is categorized based on the median values of the sample variables. Firms below the median were classified as small-scale, while those above the median were categorized as large-scale. The codes for categories of heavily polluting industries among listed companies are B06 to B12, C13, C15, C17, C19, C22, C25 to C32, D44, D45. Robust *t*-statistics are in parentheses, and \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively. The coefficient of Fisher's Permutation test represents the difference in the coefficient of EU between different sub-groups, and the number of resampling iterations is 1000.

#### 4.4.2. Pollution Heterogeneity

We further divide the sample into heavily polluting industries and non-heavily polluting industries based on the results released by the Ministry of Environmental Protection. The regression results of subsamples are shown in columns (3) and (4) in Table 6, respectively. Both of the coefficients of EU are significantly negative at the 1% level, indicating that EU contributes to reducing corporate carbon emission regardless of polluting heterogeneity. Similarly, the *p*-value for Fisher's Permutation test is 0.467, indicating that there is no significant difference in the impact of EU on carbon emission between heavily polluting enterprises and non-heavily polluting enterprises.

#### 4.4.3. Ownership Heterogeneity

In this study, we also categorize the sample into SOEs and N-SOEs. The results of grouped regressions are listed in columns (5) and (6). Obviously, the coefficients of EU are significantly negative at the 1% level regardless of ownership heterogeneity, consistent with our baseline results. Moreover, the *p*-value for Fisher's Permutation test is significant and positive, indicating that the negative of EU on carbon emission is more pronounced in N-SOEs. Compared to SOEs, N-SOEs are more flexible decision-making adjustments, enabling them to adopt new technologies in a timely manner and reduce carbon emission. Moreover, the heterogeneity is attributed to SOEs' tendency toward greenwashing under uncertainty [18]—which buffers their production from contraction—whereas N-SOEs, lacking such institutional shielding, respond through tangible operational cutbacks, resulting in greater emission reductions.

### 5. Conclusions and Recommendations

In the face of volatile environmental risks and policies, it has become increasingly necessary to explore the impact of EU on corporate decision-making. Therefore, we investigate how EU affects corporate carbon emission using the data of Chinese non-financial companies listed on the Shanghai and Shenzhen stock markets from 2010 to 2023. We further conduct the heterogeneity analysis in terms of scale differences, pollution differences and ownership differences. The mechanism by which EU influences carbon emission is also performed from the perspective of firm innovation and financing constraints. The main conclusions are derived: Firstly, EU has a significant negative impact on carbon emission. Secondly, EU affects carbon emission through innovation and financing constraints. Finally, the heterogeneity results show that the impact of EU on carbon emission is more pronounced in non-state-owned enterprises.

Based on the above findings, twofold policy recommendations for carbon reduction are provided as follows, which not only respond to the impact of EU but also guide enterprises to transform from passive decarbonization to active and high-quality decarbonization:

Firstly, active carbon reduction efforts rely on innovation. Thus, the government should formulate incentive and support policies to encourage enterprises to pursue technological innovation and apply new technologies to achieve sustainable development. Specifically, the government can increase financial support for corporate low-carbon R&D activities, and improve the intellectual property protection system for new green technologies to stimulate the innovation vitality of enterprises. Furthermore, it is necessary to strengthen the construction of innovation platforms, promote the cooperation between enterprises, universities and research institutes, and accelerate the transformation and application of low-carbon technological achievements.

Secondly, this passive decarbonization pathway is fragile because it is driven by low capacity-utilization, not by a permanent reduction in production capacity. Consequently, the emission reduction is easily reversible. When the financing constraint eases, firms

can return to full capacity, and emission will rebound accordingly. To prevent this, the government should implement conditional financing policies that require firms to improve their energy efficiency per unit of capacity, promoting the transformation of the passive idling of capacity into active decarbonization.

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