Macrothink Institute™

**Business Management and Strategy**
ISSN 2157-6068
2026, Vol. 17, No. 2

# Green Finance and Carbon Emissions in China: The Mediating Role of Green Innovation

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Received: August 25, 2026 Accepted: November 13, 2026 Published: November 16, 2026

doi:10.5296/bms.v17i2.23999 URL: https://doi.org/10.5296/bms.v17i2.23999

**Abstract**

This study examines whether green finance is associated with lower carbon emissions in China and whether green technological innovation serves as a transmission channel. Using a balanced panel of 30 Chinese provincial-level regions over 2011–2021 (330 province-year observations), we estimate two-way fixed-effects models with standard errors clustered at the province level. Green finance is measured by an entropy-weighted index covering green credit, green insurance, green investment and green support, and green technological innovation by green patent applications per 10,000 people. The total effect of green finance on log per-capita $CO_2$ emissions is −0.3322 ($p < 0.05$). Green finance is positively associated with green technological innovation ($a = 5.4479$, $p < 0.05$), which is in turn negatively associated with emissions ($b = -0.0370$, $p < 0.05$). The indirect effect ($a \times b = -0.2017$) accounts for about 61% of the total effect, and its province-block bootstrap 95% confidence interval [−0.3824, −0.0286]

excludes zero. The indirect effect remains negative and statistically distinguishable from zero across 21 alternative specifications, a province-level permutation test and several alternative inference methods. The transmission is strongest in eastern China, weaker in central China and not statistically detectable in the western and northeastern regions. The findings suggest that green finance supports China's low-carbon transition mainly by fostering green innovation, which calls for innovation-oriented and regionally differentiated green-finance policies.

**Keywords:** green finance, carbon emissions, green technological innovation, mediation effect, regional heterogeneity

## 1. Introduction

### *1.1 Background of Study*

Over the past four decades, China's economy has grown rapidly, but this growth has relied heavily on fossil energy and has placed considerable pressure on resources and the environment. China's $CO_2$ emissions rose from roughly 8.83 billion tons in 2011 to about 9.90 billion tons in 2020, the largest national total in the world, and energy use remains the dominant source of emissions across economic sectors (Harun et al., 2021). In September 2020, China pledged at the 75th session of the UN General Assembly to reach peak emissions before 2030 and carbon neutrality before 2060, and these "dual-carbon" targets were written into national planning in 2021 (Xue et al., 2023). Reconciling growth with emission reduction has therefore become a central policy objective, in line with the wider international shift toward green and low-carbon development (Chen et al., 2020).

Finance is a key lever in this transition because the allocation of capital determines which technologies and industries expand. In 2016, the People's Bank of China and six other ministries issued the Guiding Opinions on Building a Green Financial System, which describe green finance as financial services that support environmental improvement, climate mitigation and resource efficiency through instruments such as green credit, green bonds, green insurance, green funds and carbon-finance products (Xue et al., 2023). Green finance was subsequently given a prominent place in the 14th Five-Year Plan. By the end of 2021, the outstanding balance of green loans in China had reached about 15.9 trillion yuan, and green-bond issuance in that year exceeded 600 billion yuan. Whether this rapid expansion has translated into lower emissions, and through which channels, remains an empirical question. This study addresses it with provincial panel data, focusing on the role of green technological innovation and on differences across regions.

### *1.2 Problem Statement*

Green finance is widely expected to support the low-carbon transition, yet the empirical evidence on how strongly it reduces emissions, and why, remains limited. Most provincial studies estimate a direct association between green-finance indicators and emissions; fewer examine the channel through which this association arises or test the indirect effect with formal statistical inference. Moreover, Chinese regions differ markedly in financial depth, industrial structure and innovation

capacity, so a single national estimate may conceal substantial heterogeneity. Without clearer evidence on these points, policymakers cannot judge whether expanding the volume of green finance is sufficient or whether its effectiveness depends on complementary innovation capacity. This study therefore examines the association between green finance and per-capita carbon emissions, tests whether green technological innovation transmits this association, and investigates how it differs across regions and green-finance instruments.

### *1.3 Research Objectives*

1. To examine the association between green-finance development and per-capita carbon emissions across Chinese provinces.

2. To test whether green technological innovation mediates this association.

3. To assess whether the association and its innovation channel differ across China's regions.

### *1.4 Research Questions*

1. Is green-finance development associated with lower per-capita carbon emissions in Chinese provinces?

2. Does green technological innovation act as a mediating channel between green finance and carbon emissions?

3. Do the total and indirect effects of green finance differ across China's eastern, central, western and northeastern regions?

### *1.5 Significance of the Study*

This study makes three contributions. First, it provides provincial evidence on the emission effect of green finance using a multidimensional index that covers credit, insurance, investment and government support rather than a single instrument. Second, it identifies green technological innovation as a transmission channel and tests the indirect effect directly, using province-block bootstrap confidence intervals, a permutation test and inference methods suited to a moderate number of clusters. Third, by comparing regions and individual green-finance dimensions, it shows where, and through which instruments, green finance is most closely associated with emission reduction. These results are relevant to the design of green-finance policies that support China's dual-carbon targets and the UN Sustainable Development Goals, and to other emerging economies that are building green financial systems.

## 2. Literature Review

The literature relevant to this study falls into four strands: work on the concept and development of green finance, research on the measurement and drivers of carbon emissions, empirical studies of the emission effects of green finance, and studies linking green finance to green innovation. The last strand provides the theoretical basis for the mechanism tested in this paper and is discussed in Section 2.4.

### *2.1 Literature Research on Green Finance*

Early work used the term "environmental finance" to describe the use of financial tools to manage environmental risk and fund environmental improvement. The 1992 statement by banks on the environment and sustainable development issued under the United Nations Environment Programme, and Salazar's (1998) discussion of environmental finance as a bridge between the financial and environmental domains, are early examples (Gilbert & Zhou, 2017). Labatt and White (2002) described environmental finance as the application of market-based instruments to improve environmental quality and to transfer environmental risk. The 2016 G20 Green Finance Synthesis Report later offered the first widely used official definition, describing green finance as the financing of investments that provide environmental benefits in support of sustainable development; since then, the terms environmental, sustainable and green finance have often been used interchangeably (Ozili, 2022). In this study, green finance refers specifically to financial instruments and public support directed at environmentally beneficial activities, which distinguishes it from the broader notion of environmental finance that also covers environmental risk management.

Research on China has examined how these instruments should be designed and what they achieve. Tao et al. (2022) argue for coordinating fiscal and financial tools to mobilise low-carbon investment; W. Zhang et al. (2022) find that green finance improves carbon-emission efficiency; Li and Umair (2023) relate green-finance development goals to renewable-energy deployment; and Yin and Xu (2022) analyse the coupling between green finance and economic growth. Lee and Lee (2022) construct a multidimensional green-finance index for 30 provinces and show that green-finance development raises green total factor productivity, an approach close to the composite index used in this study.

### *2.2 Literature Research on Carbon Emissions*

A large body of work measures carbon emissions and decomposes their drivers. Wang and Yan (2022) attribute changes in fossil-fuel $CO_2$ emissions to population, output, energy intensity and related factors and examine their decoupling from growth, while other studies focus on particular sectors, such as transport (Xu et al., 2022), or on the role of industrial upgrading (Zhu, 2022). Decomposition methods are widely used: Zhao et al. (2022) analyse the drivers of decoupling between economic development and emissions in China, and Y. Zhang et al. (2022) document emission differences and spatial heterogeneity across China's eight economic regions. Time-series methods such as Granger causality and cointegration tests have been applied to the largest emitters to study the links between emissions, energy use and population (Ortega-Ruiz et al., 2022). Together, these studies show that energy structure, economic development, urbanisation and technology shape emissions, which motivates the control variables used in this study. Following this literature, provincial emissions are estimated here from fossil-fuel consumption and analysed in per-capita terms.

### *2.3 Literature Review on the Impact of Green Finance on Carbon Emissions*

Empirical studies generally find that green finance is associated with lower emissions or better environmental quality, although the size of the effect and its mechanism vary. Michaelowa et al. (2019) argue that well-designed carbon markets help sustain the low-carbon transition, Wan and Sheng (2022) show for Chinese provinces that green investment and clean-energy consumption are linked to lower emissions, and Doğanlar et al. (2021) find for Turkey that financial development affects energy use and emissions in the long run. For China, Bai et al. (2022) report that green-finance development reduces $CO_2$ emissions, Zhou et al. (2020) find that green finance improves provincial environmental quality, and Gan and Voda (2023) and Ran et al. (2023) show that green finance lowers carbon-emission intensity and improves carbon-emission efficiency. Li et al. (2022) find that green finance and the low-carbon economy reinforce each other in the eastern and central regions but not in the west, which suggests that the effect depends on regional conditions. Related policy studies point in a similar direction; for example, Qian et al. (2021) show that the smart-city pilot promotes urban green growth, illustrating how policy and technology jointly shape environmental outcomes.

Two gaps remain. First, most studies estimate a direct association and rarely examine the channel through which green finance affects emissions, or test the indirect effect formally. Second, evidence on how such a channel differs across regions and across green-finance instruments is scarce. This study addresses both gaps using panel data for 30 Chinese provinces.

### *2.4 Theoretical Mechanism and Hypotheses*

Green finance can influence carbon emissions through two broad channels. The first is a capital-allocation channel: by lowering the cost of funds for environmentally beneficial projects and raising the cost, or reducing the availability, of funds for carbon-intensive activities, green finance shifts investment toward cleaner industries and away from high-emission production (Zhou, 2022). The second is an innovation channel, which is the focus of this study.

Green innovation projects face particularly severe financing constraints. They require long development periods, their returns are uncertain and partly accrue to other firms, and their main assets are intangible and difficult to pledge as collateral. Firm-level evidence for China shows that financing constraints significantly reduce green innovation and that green-finance policies ease these constraints (Yu et al., 2021). Green credit policy has also been found to raise green patenting in heavily polluting firms, because tighter credit for polluting activities raises the expected cost of non-compliance and strengthens the incentive to innovate (Hu et al., 2021). Green insurance spreads environmental and technological risks, and government green support provides subsidies and guarantees that reduce the private cost of green research and development. At the regional level, Irfan et al. (2022) find that green finance promotes green innovation in China, and Wang et al. (2022) document long-run links between green finance, green innovation and environmental performance in developing countries. Accordingly, the following hypotheses are proposed:

H1: Green-finance development is associated with lower per-capita carbon emissions.

H2: Green-finance development is positively associated with green technological innovation.

Green innovation, in turn, reduces emissions by lowering energy use per unit of output, by enabling the substitution of fossil fuels with cleaner energy and by improving production and abatement technologies (Zakari et al., 2022). The finding of Lee and Lee (2022) that green finance raises green total factor productivity is consistent with this technology-based pathway. Combining the two links yields:

H3: Green technological innovation mediates the association between green finance and carbon emissions.

Finally, the conversion of green funding into effective innovation depends on regional absorptive capacity, including research infrastructure, human capital and industrial structure, which differ greatly across China (Li et al., 2022). Hence:

H4: The innovation-mediated association between green finance and carbon emissions is stronger in regions with greater innovation capacity, such as eastern China.

## 3. Research Methodology

### *3.1 Variables Description*

#### 3.1.1 Dependent Variable: Carbon Emissions (lnCE)

Provincial $CO_2$ emissions are not directly reported in official statistics. Because most emissions originate from fossil-fuel combustion, this study estimates them from the consumption of the three main fossil fuels:

$$CO_{2,it} = \alpha \cdot Coal_{it} + \beta \cdot Oil_{it} + \gamma \cdot Gas_{it}$$

Equation (1) Measurement of Carbon Emissions

where $Coal_{it}$, $Oil_{it}$ and $Gas_{it}$ denote the consumption of coal, oil and natural gas in province i and year t, and α, β and γ are the corresponding $CO_2$ conversion coefficients. Total emissions are divided by the year-end resident population to obtain per-capita emissions, and the natural logarithm of per-capita emissions (lnCE) is used as the dependent variable to reduce skewness and heteroscedasticity (Zeng & Wang, 2023; Zhao et al., 2022; Zheng et al., 2022). Carbon-emission intensity ($CO_2$ per unit of GDP) is used as an alternative outcome in the robustness analysis.

#### 3.1.2 Core Explanatory Variable: Green Finance Index (GF)

No single official statistic captures green-finance development at the provincial level. Following the Guiding Opinions on Building a Green Financial System, which identify credit,

insurance and investment as core components of green finance, and the multidimensional approach of Lee and Lee (2022), this study constructs a composite index (GF) from four dimensions. Green credit captures the orientation of bank lending toward environmentally friendly activities; green insurance is proxied by the development of agricultural insurance; green investment reflects investment in environmental protection; and green support reflects government fiscal backing for environmental protection.

The dimension weights are determined by the entropy method, which assigns larger weights to indicators that vary more across observations and therefore carry more information. Let $x_{ij}$ denote the value of indicator j for observation i (a province-year), with n observations in total. Indicators are standardised over the full 2011–2021 sample so that index values are comparable over time. Positive and negative indicators are standardised, respectively, as:

$$x'_{ij} = (x_{ij} - min\ x_j)/(max\ x_j - min\ x_j), \quad x'_{ij} = (max\ x_j - x_{ij})/(max\ x_j - min\ x_j)$$

Equation (2) Standardisation of Green-Finance Indicators

The share of each observation, the information entropy of each indicator and the resulting weight are then computed as:

$$p_{ij} = x'_{ij}/\Sigma_i x'_{ij}, \quad e_j = -(1/ln\ n)\Sigma_i p_{ij} ln\ p_{ij}, \quad w_j = (1 - e_j)/\Sigma_j(1 - e_j)$$

Equation (3) Entropy Weights

Finally, the index is obtained as $GF_{it} = \Sigma_j w_j x'_{ijt}$, which lies between 0 and 1, with higher values indicating more developed green finance. To check that the results do not depend on the entropy weights, the robustness analysis re-estimates the model with an equally weighted four-dimension index and an equally weighted three-dimension index, and Section 4.6 examines each dimension separately.

3.1.3 Mediating Variable: Green Technological Innovation (GTI)

Green technological innovation is measured by the number of green patent applications (invention and utility-model patents combined) per 10,000 resident population. Scaling by population removes the mechanical association between patent counts and provincial size, while keeping the variable in levels gives the coefficients a direct interpretation: path a measures the change in green patent applications per 10,000 people associated with a change in GF, and path b measures the proportional change in per-capita emissions associated with one additional application per 10,000 people. Three alternative measures are used in the robustness analysis: green invention patents only, the logarithm of total green patent applications, and ln(1 + green patent density).

3.1.4 Control Variables

Two control variables enter all main specifications. Economic development is measured by the natural logarithm of per-capita gross regional product (lnPGDP), and urbanisation (URB) by the share of the urban population in the resident population (%). Two further controls are added in the robustness analysis: trade openness (OPEN), measured as total imports and exports divided by GDP, and energy structure (ENG), measured as the share of coal in total energy consumption. Province fixed effects absorb time-invariant regional characteristics such as resource endowment and geography, and year fixed effects absorb nationwide macroeconomic and policy shocks. Table 1 summarises the variable definitions.

Table 1. Variable definitions

| Role | Variable | Definition |
|---|---|---|
| Dependent variable | lnCE | ln(per-capita $CO_2$ emissions) |
| Core explanatory variable | GF | Entropy-weighted index of green credit, green insurance, green investment and green support |
| Mediating variable | GTI | Green patent applications per 10,000 people (levels) |
| Control variable | lnPGDP | ln(per-capita gross regional product) |
| Control variable | URB | Urban population / resident population × 100 |
| Robustness control | OPEN | Total imports and exports / GDP |
| Robustness control | ENG | Coal consumption / total energy consumption |

*3.2 Modelling Design*

3.2.1 Benchmark Regression Model

The total effect of green finance on carbon emissions is estimated with a two-way fixed-effects model:

$$lnCE_{it} = \alpha_0 + c \cdot GF_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Equation (4) Basic Regression Model

where i and t index provinces and years, $X_{it}$ is the vector of control variables (lnPGDP and URB), $\mu_i$ and $\lambda_t$ are province and year fixed effects, and $\varepsilon_{it}$ is the error term. The coefficient c captures the total effect of green finance on per-capita emissions. Because the 30 provinces are observed repeatedly, the errors are likely to be serially correlated within provinces; standard errors are therefore clustered at the province level (30 clusters) in all specifications.

3.2.2 Mediation Model

To examine whether green technological innovation transmits the effect of green finance to carbon emissions, two further equations are estimated (Gan & Voda, 2023; Ran et al., 2023):

$$GTI_{it} = \beta_0 + a \cdot GF_{it} + \theta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Equation (5) Mediation Effects Model (1)

$$lnCE_{it} = \delta_0 + c' \cdot GF_{it} + b \cdot GTI_{it} + \varphi' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Equation (6) Mediation Effects Model (2)

Equation (5) estimates path a, the association between green finance and green innovation. Equation (6) estimates path b, the association between green innovation and emissions holding green finance constant, together with the direct effect c′. Because Equations (4)–(6) are estimated by OLS on the same sample with the same controls and fixed effects, the total effect decomposes exactly as c = c′ + a × b, where a × b is the indirect (mediated) effect.

Following current practice in mediation analysis, the significance of the indirect effect is assessed directly rather than inferred from the separate significance of a and b (Preacher & Hayes, 2008; Zhao et al., 2010). Three procedures are used. First, a province-block (cluster) bootstrap resamples entire provinces with replacement 20,000 times, re-estimates Equations (5) and (6) in each draw and reports percentile and bias-corrected confidence intervals for a × b; a second version also recomputes the entropy weights of the GF index within each draw, so that the intervals reflect the uncertainty arising from index construction. Second, a province-level permutation test randomly reassigns the complete GF time path across provinces 5,000 times to obtain the distribution of a, a × b and c under the null hypothesis of no association. Third, because 30 clusters is a moderate number, p-values for each path are also computed with the CR1 small-sample correction, with Driscoll–Kraay standard errors that allow for cross-sectional dependence (Driscoll & Kraay, 1998), and with the wild cluster bootstrap using Rademacher and Webb weights (Cameron et al., 2008; Webb, 2023).

*3.3 Data Source*

The sample is a balanced panel of 30 provincial-level regions in mainland China from 2011 to 2021, yielding 330 province-year observations; Hong Kong, Macau, Taiwan and Tibet are excluded because of data unavailability. Energy-consumption data are taken from the China Energy Statistical Yearbook. Green-finance and control-variable data are compiled from the China Statistical Yearbook, the China Environmental Statistics Yearbook, the China Industrial Statistics Yearbook, the China Insurance Yearbook and provincial statistical yearbooks, and green-patent data are obtained from the China National Intellectual Property Administration. Variables that were missing for some province-years in the original compilation were completed during data preparation, so that all variables are available for every province and year. All estimations are performed in Stata 18.

## 4. Empirical Results and Analysis

This section reports the benchmark estimates of the total effect of green finance on carbon emissions (Section 4.1), the mediation analysis (Section 4.2), formal inference for the indirect effect (Section 4.3), robustness tests (Section 4.4), and heterogeneity across regions and green-finance dimensions (Sections 4.5 and 4.6). All regressions use the balanced panel of 330 province-year observations unless stated otherwise.

### *4.1 Benchmark Regression*

Table 2. Benchmark model regression results

| Variables | lnCE (1) | lnCE (2) |
|---|---|---|
| GF | −0.5796** | −0.3322** |
| | (−2.09) | (−2.18) |
| lnPGDP | | −0.3265* |
| | | (−1.69) |
| URB | | 0.0153* |
| | | (1.85) |
| Province effects | Yes | Yes |
| Year effects | Yes | Yes |
| N | 330 | 330 |
| Clusters | 30 | 30 |
| Within $R^2$ | 0.0497 | 0.1060 |
| $R^2$ | 0.9781 | 0.9794 |

Note: t-statistics in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the province level.

Table 2 reports the estimates of Equation (4). Without controls (column 1), the GF coefficient is −0.5796 and significant at the 5% level. After lnPGDP and URB are added (column 2), the coefficient falls in magnitude to −0.3322 but remains significant at the 5% level (t = −2.18). Because GF lies between 0 and 1 and the dependent variable is in logarithms, the column (2) estimate implies that a 0.1-point increase in the green-finance index is associated with approximately 3.3% lower per-capita $CO_2$ emissions, holding economic development, urbanisation and the fixed effects constant. H1 is therefore supported. Column (2) is used as the estimate of the total effect c in the mediation analysis.

Among the controls, lnPGDP is negatively associated with per-capita emissions (−0.3265, significant at the 10% level), which is consistent with the gradual decoupling of emissions from income as provincial economies mature. URB has a positive coefficient (0.0153, significant at the 10% level): a one-percentage-point rise in the urbanisation rate is associated with roughly 1.5% higher per-capita emissions, reflecting the energy demand of urban construction, transport

and residential consumption. The within $R^2$ of 0.106 is modest because the province and year fixed effects absorb most of the variation in emissions (overall $R^2 = 0.979$); the GF coefficient is therefore identified from within-province changes over time relative to the national trend.

*4.2 Mediation Analysis*

Table 3. Green technological innovation as a mediator

| Variables | GTI (1) | lnCE (2) |
|---|---|---|
| GF | 5.4479** | −0.1304** |
| | (2.30) | (−2.06) |
| GTI | | −0.0370** |
| | | (−2.16) |
| lnPGDP | 3.1479** | −0.2099 |
| | (2.73) | (−0.99) |
| URB | −0.3445*** | 0.0025 |
| | (−5.99) | (0.21) |
| Province effects | Yes | Yes |
| Year effects | Yes | Yes |
| N | 330 | 330 |
| Clusters | 30 | 30 |
| Within $R^2$ | 0.6177 | 0.1412 |
| $R^2$ | 0.9476 | 0.9802 |

Note: t-statistics in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the province level. Indirect effect $a \times b = 5.4479 \times (-0.0370) = -0.2017$; total effect $c = c' + a \times b = -0.1304 + (-0.2017) = -0.3321$ ($\approx -0.3322$ in Table 2; the difference is due to rounding).

Column (1) of Table 3 reports Equation (5). The GF coefficient is 5.4479 and significant at the 5% level ($t = 2.30$), indicating that provinces with more developed green finance exhibit more green innovation: a 0.1-point increase in GF is associated with about 0.54 additional green patent applications per 10,000 people. H2 is therefore supported. lnPGDP is positively associated with green innovation, whereas URB has a negative coefficient once income is controlled for, suggesting that urban expansion that is not accompanied by income growth does not by itself raise green patenting.

Column (2) reports Equation (6). Holding green finance constant, GTI is negatively associated with per-capita emissions ($b = -0.0370$, significant at the 5% level): one additional green patent application per 10,000 people is associated with approximately 3.7% lower per-capita emissions. The direct effect of GF falls from −0.3322 to −0.1304 but remains significant at the 5% level ($t = -2.06$).

The total effect therefore decomposes into a direct effect of −0.1304 and an indirect effect of −0.2017, so the innovation channel accounts for about 60.7% of the total association between green finance and per-capita emissions. Because the direct, indirect and total effects share the same sign, the pattern corresponds to complementary partial mediation in the classification of Zhao et al. (2010): green technological innovation is the main, but not the only, channel through which green finance is associated with lower emissions, which supports H3.

*4.3 Inference for the Indirect Effect*

4.3.1 Bootstrap Confidence Intervals

Table 4. Bootstrap test of the indirect effect

| Method | a × b | Boot SE | 95% percentile CI | 90% percentile CI | 95% bias-corrected CI |
|---|---|---|---|---|---|
| Baseline bootstrap | −0.2017 | 0.0900 | [−0.3824, −0.0286] | [−0.3512, −0.0548] | [−0.4105, −0.0362] |
| Index re-estimated bootstrap | −0.2017 | 0.0865 | [−0.3742, −0.0321] | [−0.3440, −0.0605] | [−0.4218, −0.0445] |

Note: Based on 20,000 province-block resamples. In the index re-estimated bootstrap, the entropy weights of the GF index are recomputed within each resample.

Table 4 reports the province-block bootstrap results. The 95% percentile confidence interval for the indirect effect is [−0.3824, −0.0286] and the 95% bias-corrected interval is [−0.4105, −0.0362]; neither contains zero, so the indirect effect is statistically significant at the 5% level. When the entropy weights are re-estimated in every bootstrap draw, the standard error changes only slightly (0.0865 versus 0.0900) and all intervals remain strictly below zero. Uncertainty arising from the construction of the GF index therefore does not overturn the mediation result.

4.3.2 Permutation Test

Table 5. Province-path permutation test

| Statistic | Estimate | Permutation p-value |
|---|---|---|
| a (GF → GTI) | 5.4479 | 0.004 |
| a × b (indirect effect) | −0.2017 | 0.008 |
| c (total effect) | −0.3322 | 0.032 |

Note: Two-sided p-values obtained from 5,000 random province-level permutations of the GF time path.

A concern with provincial panels is that common trends in green finance, green patenting and emissions could generate spurious associations. The permutation test addresses this concern by randomly assigning the complete GF time path of one province to another while keeping the outcome and mediator unchanged, which preserves the time-series structure of each variable but breaks any genuine province-specific link. As Table 5 shows, the observed estimates are extreme relative to the permutation distribution: the p-values are 0.004 for path a, 0.008 for the indirect effect and 0.032 for the total effect. The associations are therefore unlikely to reflect a shared national trend.

4.3.3 Alternative Inference Methods

Table 6. p-values under alternative inference methods

| Path | Coefficient | CR1 | CR1 (full FE df) | Driscoll–Kraay | Wild (Rademacher) | Wild (Webb) |
|---|---|---|---|---|---|---|
| a: GF → GTI | 5.4479 | 0.029 | 0.037 | 0.017 | 0.040 | 0.036 |
| b: GTI → lnCE | −0.0370 | 0.040 | 0.049 | <0.001 | 0.044 | 0.046 |
| c: total effect | −0.3322 | 0.037 | 0.044 | 0.021 | 0.041 | 0.043 |
| c′: direct effect | −0.1304 | 0.048 | 0.056 | 0.032 | 0.051 | 0.053 |

Note: Columns 3–7 report two-sided p-values. CR1 = cluster-robust standard errors with small-sample correction; "full FE df" additionally counts the fixed effects in the degrees-of-freedom correction.

Table 6 shows that the conclusions do not depend on the choice of standard errors. Paths a and b and the total effect c are significant at the 5% level under all five methods, including the wild cluster bootstrap, which performs well when the number of clusters is moderate (Cameron et al., 2008; Webb, 2023), and Driscoll–Kraay standard errors, which allow for cross-sectional dependence between provinces. The direct effect c′ is less precisely estimated, with p-values between 0.032 and 0.056. The evidence for a direct effect of green finance is therefore borderline, whereas the evidence for the innovation-mediated component is consistent across methods.

*4.4 Robustness Tests*

Table 7. Robustness test results

| Test | N | a | b | c | a × b | 95% CI | 90% CI |
|---|---|---|---|---|---|---|---|
| Baseline specification | 330 | 5.4479** | −0.0370** | −0.3322** | −0.2017 | [−0.3824, −0.0286] | [−0.3512, −0.0548] |
| Equal weights (same four dimensions) | 330 | 4.0126*** | −0.0360* | −0.3263** | −0.1444 | [−0.2785, −0.0152] | [−0.2564, −0.0348] |
| Adding trade openness (OPEN) | 330 | 3.8894** | −0.0404** | −0.3067* | −0.1572 | [−0.3041, −0.0188] | [−0.2795, −0.0392] |
| Adding energy structure (ENG) | 330 | 4.9102** | −0.0285* | −0.2894* | −0.1399 | [−0.2712, −0.0145] | [−0.2490, −0.0335] |
| Invention patents only | 330 | 4.4664* | −0.0449** | −0.3322** | −0.2005 | [−0.3810, −0.0265] | [−0.3502, −0.0530] |
| ln(total green patents) | 330 | 0.4054** | −0.3820** | −0.3322** | −0.1549 | [−0.2980, −0.0195] | [−0.2742, −0.0401] |
| ln(1 + patent density) | 330 | 0.2949* | −0.4510** | −0.3322** | −0.1330 | [−0.2584, −0.0142] | [−0.2371, −0.0320] |
| Per-capita GDP in levels | 330 | 3.1834** | −0.0385* | −0.2508* | −0.1226 | [−0.2395, −0.0128] | [−0.2198, −0.0295] |
| Per-capita GDP = GDP/population | 330 | 5.4009** | −0.0366** | −0.3267** | −0.1977 | [−0.3765, −0.0270] | [−0.3460, −0.0525] |
| Emission intensity as outcome | 330 | 5.4479** | −0.0379** | −0.3412** | −0.2063 | [−0.3912, −0.0298] | [−0.3595, −0.0568] |
| GF winsorized at 1% | 330 | 4.7679** | −0.0377** | −0.3009* | −0.1799 | [−0.3442, −0.0235] | [−0.3165, −0.0468] |
| Excluding observations using 2017 GF | 300 | 5.4947** | −0.0361* | −0.3378** | −0.1984 | [−0.3780, −0.0268] | [−0.3474, −0.0526] |
| Excluding Beijing | 319 | 2.4354* | −0.0391* | −0.2356* | −0.0952 | [−0.1865, −0.0102] | [−0.1710, −0.0234] |
| Province-specific linear trends | 330 | 3.2140* | −0.0342* | −0.2645* | −0.1099 | [−0.2148, −0.0118] | [−0.1972, −0.0268] |
| Sample restricted to 2013–2021 | 270 | 3.6456** | −0.0429** | −0.5312** | −0.1563 | [−0.3015, −0.0192] | [−0.2772, −0.0398] |
| Lag structure (2,1,2) | 270 | 4.0926** | −0.0380** | −0.3277** | −0.1557 | [−0.2998, −0.0189] | [−0.2756, −0.0395] |
| Excluding top-4 patent provinces | 286 | 3.1280* | −0.0448* | −0.2790* | −0.1401 | [−0.2715, −0.0150] | [−0.2492, −0.0338] |
| Excluding four municipalities | 286 | 2.9473* | −0.0420* | −0.2724* | −0.1238 | [−0.2412, −0.0131] | [−0.2214, −0.0301] |
| Excluding 2020–2021 | 270 | 3.9337* | −0.0284* | −0.2480* | −0.1117 | [−0.2185, −0.0119] | [−0.2005, −0.0272] |
| Region × year fixed effects | 330 | 4.4888* | −0.0315* | −0.3683* | −0.1414 | [−0.2740, −0.0154] | [−0.2516, −0.0342] |
| Adding OPEN and ENG | 330 | 3.4406* | −0.0320* | −0.2590* | −0.1101 | [−0.2150, −0.0118] | [−0.1974, −0.0269] |
| Province trends + ln(1 + density) | 330 | 0.2810* | −0.3950* | −0.2512* | −0.1110 | [−0.2168, −0.0120] | [−0.1990, −0.0271] |

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels. In every specification a × b equals the product of a and b, and neither the 95% nor the 90% bootstrap confidence interval contains zero. Coefficients a and b are not comparable in magnitude with the baseline in rows in which GTI is measured in logarithms.

Table 7 reports 21 robustness tests grouped by the concern they address. In every specification, path a is positive, path b is negative, the total effect c is negative, and both the 95% and 90% bootstrap confidence intervals for a × b lie strictly below zero.

*Measurement of green finance.* Replacing the entropy weights with equal weights on the same four dimensions, winsorising GF at the 1% level and excluding the 30 observations whose GF values are based on 2017 indicator data all leave the conclusions unchanged; the indirect effect ranges from −0.1444 to −0.1984. The results therefore do not hinge on the weighting scheme or on extreme index values.

*Measurement of green innovation and carbon emissions.* Using green invention patents only, the logarithm of total green patents or ln(1 + patent density) as the mediator yields indirect effects between −0.1330 and −0.2005. Replacing per-capita emissions with carbon-emission intensity produces an indirect effect of −0.2063, almost identical to the baseline. The mediation result is thus not specific to one measure of innovation or of emissions.

*Omitted variables and control specification.* Adding trade openness, energy structure or both, and measuring economic development as per-capita GDP in levels or as GDP divided by population, changes the indirect effect to between −0.1101 and −0.1977 but does not alter its sign or significance. The attenuation when ENG is added is expected, because part of the association between innovation and emissions operates through the substitution of coal with cleaner energy, which ENG partly absorbs.

*Sample composition.* Excluding Beijing, the four municipalities, or the four provinces with the highest green-patent density reduces the indirect effect to between −0.0952 and −0.1401. The largest change occurs when Beijing alone is excluded, where the indirect effect roughly halves: Beijing combines highly developed green finance, very high patent density and declining emissions, and therefore contributes substantially to the magnitude of the baseline estimate. The sign and significance of the indirect effect are nevertheless preserved. Restricting the sample to 2013–2021, or excluding the COVID-19 years 2020–2021, also leaves the conclusions intact.

*Unobserved trends, timing and endogeneity.* Province-specific linear trends absorb differential long-run trajectories, such as faster structural transformation in some provinces, and region × year fixed effects absorb region-specific shocks in each year. A dynamic specification with lag orders (2, 1, 2), which relies on lagged values and therefore loses the first two years of data, reduces the concern that contemporaneous reverse causality drives the results. The indirect effect remains between −0.1099 and −0.1557 in these specifications.

Overall, the innovation-mediated component is the most stable finding. Its magnitude varies between about −0.10 and −0.21 depending on the specification, and in several specifications the individual path coefficients are significant only at the 10% level, so the precise size of the effect should be interpreted with caution. Its sign and its statistical distinction from zero, however, are consistent across all 21 tests.

*4.5 Regional Heterogeneity Analysis*

To examine regional heterogeneity, the sample is divided into the four economic regions defined by the National Bureau of Statistics: eastern (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan), central (Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan), western (Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang) and northeastern (Liaoning, Jilin and Heilongjiang). Equations (4)–(6) are estimated separately for each region.

Table 8. Impact of green finance on carbon emissions by region

| Variables | Eastern (1) | Central (2) | Western (3) | Northeastern (4) |
|---|---|---|---|---|
| c (total effect) | −0.5107** | −0.2840* | −0.0961 | −0.1420 |
| | (p = 0.042) | (p = 0.068) | (p = 0.659) | (p = 0.582) |
| a: GF → GTI | 7.6569** | 4.1250* | 0.8520 | 1.1040 |
| | (p = 0.038) | (p = 0.074) | (p = 0.712) | (p = 0.640) |
| b: GTI → lnCE | −0.0310*** | −0.0295** | −0.0185 | −0.0232 |
| | (p < 0.001) | (p = 0.041) | (p = 0.490) | (p = 0.415) |
| c′ (direct effect) | −0.2730** | −0.1623 | −0.0803 | −0.1164 |
| | (p = 0.042) | (p = 0.145) | (p = 0.695) | (p = 0.620) |
| a × b | −0.2377** | −0.1217* | −0.0158 | −0.0256 |
| | (p = 0.045) | (p = 0.082) | (p = 0.740) | (p = 0.685) |
| Province/year effects | Yes | Yes | Yes | Yes |
| N | 110 | 66 | 121 | 33 |
| Clusters | 10 | 6 | 11 | 3 |

Note: p-values in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. In each region c = c′ + a × b (e.g. Eastern: −0.2730 + (−0.2377) = −0.5107; Central: −0.1623 + (−0.1217) = −0.2840).

Table 8 shows a clear east–west gradient. In the eastern region, all components are significant: the total effect is −0.5107, green finance is strongly associated with green innovation (a = 7.6569), innovation is strongly associated with lower emissions (b = −0.0310, p < 0.001), and the indirect effect of −0.2377 accounts for about 47% of the total effect. In the central region, the total effect (−0.2840) and the indirect effect (−0.1217) are significant at the 10% level and path b at the 5% level, while the direct effect is insignificant, so the association there runs mainly through innovation. In the western and northeastern regions, none of the coefficients is statistically significant, and both path a and the indirect effect are an order of magnitude smaller than in the east. These patterns are consistent with H4.

Two caveats apply. First, the regional regressions rely on a small number of clusters, particularly in the central (6) and northeastern (3) subsamples, so the cluster-robust p-values for these regions are imprecise and should be regarded as indicative. Second, the differences between regions are differences in point estimates and significance; no formal test of equality

across regions is reported. The regional results nevertheless indicate that the national innovation channel is concentrated in the eastern and, to a lesser extent, the central provinces.

*4.6 Heterogeneity Across Green-Finance Dimensions*

Table 9. Results by green-finance dimension

| Treatment | a | b | c | a × b | 95% CI | 90% CI |
|---|---|---|---|---|---|---|
| Green credit (GC) | 1.6568** | −0.0371* | −0.1845** | −0.0615 | [−0.1180, −0.0085] | [−0.1082, −0.0168] |
| Green insurance (GINS) | 3.9506** | −0.0481** | −0.3120** | −0.1900 | [−0.3610, −0.0265] | [−0.3315, −0.0510] |
| Green investment (GI) | 1.4250* | −0.0390** | −0.1758* | −0.0556 | [−0.1072, −0.0074] | [−0.0981, −0.0150] |
| Green support (GS) | 1.2840* | −0.0399** | −0.1620* | −0.0512 | [−0.0992, −0.0068] | [−0.0908, −0.0138] |
| GF3: equal weights, three dimensions | 1.8511** | −0.0366* | −0.2567** | −0.0678 | [−0.1295, −0.0095] | [−0.1188, −0.0185] |

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels. Each row replaces GF with the indicated dimension sub-index.

Table 9 replaces the composite index with each of its four dimensions. All four dimensions display a positive path a, a negative path b and an indirect effect whose confidence intervals lie strictly below zero, so the innovation channel is not driven by a single component of the index. The indirect effect is largest for green insurance (−0.1900) and considerably smaller for green credit (−0.0615), green investment (−0.0556) and green support (−0.0512). Because the dimension sub-indices differ in their distributions, these magnitudes indicate relative importance only approximately.

## 5. Discussion and Conclusions

*5.1 Discussion*

5.1.1 Green Finance and Carbon Emissions

The first finding is that green-finance development is associated with lower per-capita carbon emissions across Chinese provinces. The total effect is significant under province-clustered, Driscoll–Kraay and wild-bootstrap inference and in the permutation test, and it retains its negative sign in all robustness specifications. This is consistent with earlier provincial evidence that green finance is associated with lower emissions or emission intensity in China (Bai et al., 2022; Gan & Voda, 2023; Zhou et al., 2020) and with studies reporting improvements in carbon-emission efficiency (Ran et al., 2023; W. Zhang et al., 2022).

The present results refine this literature in one respect. Once green innovation is controlled for, the direct effect of green finance shrinks by about 60% and becomes only marginally

significant (p between 0.032 and 0.056 across inference methods). Most of the association between green finance and emissions therefore operates through what green finance enables rather than through the volume of green funding as such. Because the estimates come from observational fixed-effects models, they describe conditional associations rather than causal effects; the permutation test, province-specific trends and region × year fixed effects reduce, but do not eliminate, the possibility that unobserved time-varying factors drive both green finance and emissions.

#### 5.1.2 The Mediating Role of Green Technological Innovation

The second and central finding is that green technological innovation is the main channel linking green finance to lower emissions, accounting for about 61% of the total association, with bootstrap confidence intervals that exclude zero in all specifications. This result is consistent with the financing-constraint mechanism set out in Section 2.4. Green innovation is particularly exposed to financing constraints, and firm-level evidence shows that green-finance policies relax these constraints and raise green patenting (Hu et al., 2021; Yu et al., 2021). The provincial results in this study show that the same mechanism is visible at the aggregate level and that it carries through to emissions, extending the findings of Irfan et al. (2022) on green finance and green innovation and of Lee and Lee (2022) on green productivity.

Green innovation, in turn, is likely to reduce emissions by lowering energy use per unit of output, enabling the substitution of coal with cleaner energy and improving production and abatement technologies (Zakari et al., 2022). The attenuation of path b when the coal share (ENG) is controlled for is consistent with the fuel-substitution part of this mechanism. The remaining direct component is plausibly related to capital reallocation: green-finance policies may shift investment away from carbon-intensive industries even when no new technology is developed.

#### 5.1.3 Regional Heterogeneity

The third finding is that the innovation channel is concentrated in the eastern region, weaker in the central region and statistically undetectable in the western and northeastern regions. The eastern provinces combine more developed financial markets with dense research institutions, high-technology industries and a skilled labour force, so green funding there is more readily converted into patented technologies that are then adopted in production. This explains why both path a and path b are largest in the east. The central provinces have been absorbing industrial relocation from the coast and building innovation capacity, which is consistent with a significant innovation–emission link but a weaker and less precisely estimated finance–innovation link.

In the western and northeastern regions, the economic structure is dominated by energy production, heavy industry and resource extraction, and regional innovation systems are thinner. Green finance in these regions is more likely to be directed to infrastructure, renewable-energy installation and ecological restoration, whose emission effects may take

longer to appear and are not captured by patent activity. The small number of provinces in these subsamples, especially in the northeast, also limits statistical power, so the absence of significance should not be read as evidence that green finance is ineffective there. These patterns accord with Li et al. (2022), who report that the interaction between green finance and the low-carbon economy is stronger in the eastern and central regions than in the west, and they extend that evidence by showing that the regional differences arise in the innovation channel itself.

#### 5.1.4 Differences across Green-Finance Dimensions

All four dimensions of green finance contribute to the innovation channel, but the indirect effect is largest for green insurance and much smaller for green credit, even though green credit dominates China's green-finance system in volume. This contrast suggests that the scale of an instrument does not determine its contribution to emission reduction; instruments that share risk and support innovation may be more effective per unit of development than instruments that mainly expand the volume of funding. Because the insurance dimension is measured with a relatively narrow indicator, this result should be treated as suggestive rather than conclusive.

#### 5.1.5 Policy and Practical Implications

Three implications follow. First, because most of the emission-related benefit of green finance operates through innovation, green-finance policy should explicitly target green research, development and technology adoption. Preferential lending rates, guarantee schemes and dedicated funds for low-carbon technology, together with green insurance products that cover technological and environmental risks, are likely to yield larger emission reductions than policies that only expand the volume of green loans. The performance of green finance should accordingly be assessed by its innovation and verified emission outcomes rather than only by the amount of financing issued.

Second, financial institutions could incorporate measurable carbon-performance and technology criteria into project screening, pricing and post-loan monitoring, so that green-labelled funds reach projects capable of producing durable carbon savings.

Third, regional policy should be differentiated. In the eastern region, where the innovation channel is already effective, the priority is to improve the allocation and quality of green finance and to accelerate the diffusion of green technologies. In the central region, green finance should be coordinated with efforts to strengthen local innovation capacity so that financial resources are converted into technological outcomes. In the western and northeastern regions, green finance should be combined with investment in innovation infrastructure, technology transfer from the east and stricter environmental-performance requirements for financed projects, so that green funding supports genuinely low-carbon industrial upgrading rather than the expansion of energy-intensive capacity.

5.1.6 Limitations and Directions for Future Research

This study has several limitations. First, the analysis relies on provincial aggregates and cannot trace how individual banks allocate green credit or how particular firms use green funds; firm-level data linking green financing to patents and verified emissions would allow a sharper test of the mechanism. Second, although the results are robust to fixed effects, province-specific trends, region × year effects, lagged specifications and a permutation test, the estimates remain associations, and endogeneity arising from time-varying omitted factors or reverse causality cannot be fully ruled out. Future research could exploit quasi-natural experiments, such as the Green Finance Reform and Innovation Pilot Zones established from 2017, within a difference-in-differences framework (as in Hu et al., 2021, for the green credit guidelines), or use credible instrumental variables. Third, the regional subsamples contain few provinces, which limits the precision of regional inference. Fourth, green patent counts measure the quantity rather than the quality or environmental effectiveness of innovation, and the entropy-weighted index depends on the indicators available. Future studies could use citation-weighted patents or technology-specific classifications and extend the analysis to other emerging economies.

*5.2 Conclusion*

Using a balanced panel of 30 Chinese provinces over 2011–2021, this study examines the relationship between green finance and per-capita carbon emissions and the mediating role of green technological innovation. Three conclusions emerge. First, green-finance development is associated with lower per-capita carbon emissions, with a total effect of −0.3322 that is significant across alternative inference methods and preserves its sign in 21 robustness tests. Second, green technological innovation is the main transmission channel: green finance is positively associated with green patenting ($a = 5.4479$), green patenting is negatively associated with emissions ($b = -0.0370$), and the indirect effect of −0.2017 accounts for about 61% of the total effect, with a province-block bootstrap confidence interval that excludes zero; the remaining direct effect is only marginally significant. Third, the innovation channel is strongest in the eastern region, weaker in the central region and not detectable in the western and northeastern regions, and it is present for all four dimensions of green finance, most strongly for green insurance.

These results suggest that green finance contributes to China's low-carbon transition mainly by fostering green innovation rather than through the scale of green funding alone. Strengthening the link between green financial resources and technological innovation, and adapting green-finance policy to regional differences in innovation capacity, are therefore the most promising ways to increase the contribution of green finance to China's carbon-peaking and carbon-neutrality goals.

**Acknowledgments**

Not applicable.

## Author contributions

Siyu Guan was responsible for the conceptualization of the study and drafted the manuscript. Haslindar Ibrahim was responsible for reviewing and revising the manuscript. Sibo Zhou was responsible for data collection. All authors read and approved the final manuscript.

## Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

## Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Informed consent

Obtained.

## Ethics approval

The Publication Ethics Committee of the Macrothink Institute.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

## Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

## Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

## Data sharing statement

No additional data are available.

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## References

Bai, J., Chen, Z., Yan, X., & Zhang, Y. (2022). Research on the impact of green finance on carbon emissions: Evidence from China. *Economic Research-Ekonomska Istraživanja, 35*(1), 6965–6984. https://doi.org/10.1080/1331677X.2022.2054455

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics, 90*(3), 414–427. https://doi.org/10.1162/rest.90.3.414

Chen, Y., Liu, S., Wu, H., Zhang, X., & Zhou, Q. (2020). How can Belt and Road countries contribute to glocal low-carbon development? *Journal of Cleaner Production, 256,* 120717. https://doi.org/10.1016/j.jclepro.2020.120717

Doğanlar, M., Mike, F., Kızılkaya, O., & Karlılar, S. (2021). Testing the long-run effects of economic growth, financial development and energy consumption on $CO_2$ emissions in Turkey: New evidence from RALS cointegration test. *Environmental Science and Pollution Research, 28*(25), 32554–32563. https://doi.org/10.1007/s11356-021-12661-y

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics, 80*(4), 549–560. https://doi.org/10.1162/003465398557825

Gan, C., & Voda, M. (2023). Can green finance reduce carbon emission intensity? Mechanism and threshold effect. *Environmental Science and Pollution Research, 30*(1), 640–653. https://doi.org/10.1007/s11356-022-21372-2

Gilbert, S., & Zhou, L. (2017). The knowns and unknowns of China's green finance. *The New Climate Economy, 5*, 77–80.

Harun, M., Ahmad, S. A., Sulaiman, N., & Tria, D. (2021). Sectoral energy–$CO_2$ emissions using an environmental input-output framework. *International Journal of Business and Society, 22*(2), 1066–1075.

Hu, G., Wang, X., & Wang, Y. (2021). Can the green credit policy stimulate green innovation in heavily polluting enterprises? Evidence from a quasi-natural experiment in China. *Energy Economics, 98*, 105134. https://doi.org/10.1016/j.eneco.2021.105134

Irfan, M., Razzaq, A., Sharif, A., & Yang, X. (2022). Influence mechanism between green finance and green innovation: Exploring regional policy intervention effects in China. *Technological Forecasting & Social Change, 182*, 121882. https://doi.org/10.1016/j.techfore.2022.121882

Labatt, S., & White, R. R. (2002). *Environmental finance: A guide to environmental risk assessment and financial products* (Vol. 98). John Wiley & Sons.

Lee, C.-C., & Lee, C.-C. (2022). How does green finance affect green total factor productivity? Evidence from China. *Energy Economics, 107*, 105863. https://doi.org/10.1016/j.eneco.2022.105863

Li, C., & Umair, M. (2023). Does green finance development goals affects renewable energy in China. *Renewable Energy, 203*, 898–905. https://doi.org/10.1016/j.renene.2022.12.066

Li, W., Fan, J., & Zhao, J. (2022). Has green finance facilitated China's low-carbon economic transition? *Environmental Science and Pollution Research, 29*(38), 57502–57515. https://doi.org/10.1007/s11356-022-19284-6

Michaelowa, A., Shishlov, I., & Brescia, D. (2019). Evolution of international carbon markets: Lessons for the Paris Agreement. *Wiley Interdisciplinary Reviews: Climate Change, 10*(6), e613. https://doi.org/10.1002/wcc.613

Ortega-Ruiz, G., Mena-Nieto, A., Golpe, A., & García-Ramos, J. E. (2022). $CO_2$ emissions and causal relationships in the six largest world emitters. *Renewable & Sustainable Energy Reviews, 162*, 112435. https://doi.org/10.1016/j.rser.2022.112435

Ozili, P. K. (2022). Green finance research around the world: A review of literature. *International Journal of Green Economics, 16*(1), 56–75. https://doi.org/10.1504/IJGE.2022.121837

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Qian, Y., Liu, J., Cheng, Z., & Forrest, J. Y.-L. (2021). Does the smart city policy promote the green growth of the urban economy? Evidence from China. *Environmental Science and Pollution Research, 28*, 66709–66723. https://doi.org/10.1007/s11356-021-15158-6

Ran, Q., Liu, L., Razzaq, A., Meng, Y., & Yang, X. (2023). Does green finance improve carbon emission efficiency? Experimental evidence from China. *Environmental Science and Pollution Research, 30*(16), 48288–48299. https://doi.org/10.1007/s11356-023-26427-x

Salazar, J. (1998). Environmental finance: Linking two worlds. In *Proceedings of the Workshop on Financial Innovations for Biodiversity, Bratislava* (pp. 1–15).

Tao, H., Zhuang, S., Xue, R., Cao, W., Tian, J., & Shan, Y. (2022). Environmental finance: An interdisciplinary review. *Technological Forecasting & Social Change, 179*, 121639. https://doi.org/10.1016/j.techfore.2022.121639

Wan, Y., & Sheng, N. (2022). Clarifying the relationship among green investment, clean energy consumption, carbon emissions, and economic growth: A provincial panel analysis of China. *Environmental Science and Pollution Research, 29*(6), 9038–9052. https://doi.org/10.1007/s11356-021-16170-w

Wang, Q.-J., Wang, H.-J., & Chang, C.-P. (2022). Environmental performance, green finance and green innovation: What's the long-run relationships among variables? *Energy Economics, 110*, 106004. https://doi.org/10.1016/j.eneco.2022.106004

Wang, X., & Yan, L. (2022). Driving factors and decoupling analysis of fossil fuel related-carbon dioxide emissions in China. *Fuel, 314,* 122869. https://doi.org/10.1016/j.fuel.2021.122869

Webb, M. D. (2023). Reworking wild bootstrap-based inference for clustered errors. *Canadian Journal of Economics, 56*(3), 839–858. https://doi.org/10.1111/caje.12661

Xu, H., Li, Y., Zheng, Y., & Xu, X. (2022). Analysis of spatial associations in the energy–carbon emission efficiency of the transportation industry and its influencing factors: Evidence from China. *Environmental Impact Assessment Review, 97*, 106905. https://doi.org/10.1016/j.eiar.2022.106905

Xue, Y., Ma, T., Zhuang, T., & Ma, Y. (2023). The development of green finance under the goal of carbon neutrality: A review from China's perspective. *Frontiers in Earth Science, 11*, 1123020. https://doi.org/10.3389/feart.2023.1123020

Yin, X., & Xu, Z. (2022). An empirical analysis of the coupling and coordinated development of China's green finance and economic growth. *Resources Policy, 75*, 102476. https://doi.org/10.1016/j.resourpol.2021.102476

Yu, C.-H., Wu, X., Zhang, D., Chen, S., & Zhao, J. (2021). Demand for green finance: Resolving financing constraints on green innovation in China. *Energy Policy, 153*, 112255. https://doi.org/10.1016/j.enpol.2021.112255

Zakari, A., Khan, I., Tan, D., Alvarado, R., & Dagar, V. (2022). Energy efficiency and Sustainable Development Goals (SDGs). *Energy, 239,* 122365. https://doi.org/10.1016/j.energy.2021.122365

Zeng, S., & Wang, M. (2023). Theoretical and empirical analyses on the factors affecting carbon emissions: Case of Zhejiang Province, China. *Environment, Development & Sustainability, 25*(3), 2522–2549. https://doi.org/10.1007/s10668-022-02166-3

Zhang, W., Zhu, Z., Liu, X., & Cheng, J. (2022). Can green finance improve carbon emission efficiency? *Environmental Science and Pollution Research, 29*(45), 68976–68989. https://doi.org/10.1007/s11356-022-20661-3

Zhang, Y., Yu, Z., & Zhang, J. (2022). Research on carbon emission differences decomposition and spatial heterogeneity pattern of China's eight economic regions. *Environmental Science and Pollution Research. Advance online publication.* https://doi.org/10.1007/s11356-022-21983-w

Zhao, X., Jiang, M., & Zhang, W. (2022). Decoupling between economic development and carbon emissions and its driving factors: Evidence from China. *International Journal of*

*Environmental Research and Public Health, 19*(5), 2893. https://doi.org/10.3390/ijerph19052893

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206. https://doi.org/10.1086/651257

Zheng, Y., Xiao, J., Huang, F., & Tang, J. (2022). How do resource dependence and technological progress affect the carbon-emission-reduction effect of industrial-structure transformation? An empirical study based on the rebound effect in China. *Environmental Science and Pollution Research. Advance online publication.* https://doi.org/10.1007/s11356-022-23373-6

Zhou, J. (2022). Analysis and countermeasures of green finance development under carbon peaking and carbon neutrality goals. *Open Journal of Social Sciences, 10*(2), 147–154. https://doi.org/10.4236/jss.2022.102011

Zhou, X., Tang, X., & Zhang, R. (2020). Impact of green finance on economic development and environmental quality: A study based on provincial panel data from China. *Environmental Science and Pollution Research, 27*, 19915–19932. https://doi.org/10.1007/s11356-020-08323-4

Zhu, X. (2022). Have carbon emissions been reduced due to the upgrading of industrial structure? Analysis of the mediating effect based on technological innovation. *Environmental Science and Pollution Research, 29*(36), 54890–54901. https://doi.org/10.1007/s11356-022-20818-0