



OPEN Impact of land prices on corporate carbon emission intensity

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This study examines the impact of micro-level land prices on corporate carbon emission intensity and identifies the underlying mechanisms. Using a unique dataset of Chinese industrial enterprises from 2000 to 2014, we employ a two-way fixed effects econometric model, alongside instrumental variable and Difference-in-Differences (DID) techniques, to address endogeneity concerns. Our findings reveal that a 1% increase in land prices leads to a 0.253% rise in carbon emission intensity, driven by heightened financing constraints and reduced innovation. The effects are most pronounced in central and western regions, among non-state-owned enterprises, and in industries with stricter environmental regulations or firms acquiring land through public bidding. These findings highlight critical policy implications: land market reforms to curb speculative price inflation, enhanced access to financing, and targeted support for innovation in high-impact regions and industries. By providing novel insights into the environmental impact of land price dynamics, this research offers practical guidance for balancing economic development and carbon reduction efforts.

Keywords Land price, Carbon emissions, Financing constraints, Innovation

The rapid increase in greenhouse gas (GHG) emissions due to human activities has exacerbated the global climate crisis, posing profound threats to both human safety and economic development. Among the various GHGs, carbon dioxide (CO₂) is the most significant, making carbon emission reduction a global priority¹. Recent studies have highlighted the role of economic complexity and renewable energy consumption in mitigating carbon emissions. For instance, Doğan et al.² found that structural transformation toward more sophisticated and knowledge-based production, coupled with renewable energy consumption, can help reduce environmental degradation in developed countries. Similarly, Doğan et al.³ emphasized the importance of economic complexity, trade openness, foreign direct investment (FDI), and institutional quality in sustaining economic growth while adhering to environmental commitments, such as those outlined in the Paris Agreement.

While these macro-level factors are crucial, there is a growing recognition of the need to understand micro-level determinants of carbon emissions. One such factor is corporate land prices, which can influence firms' operational costs, investment decisions, and, consequently, their carbon emission intensity. However, the impact of land prices on corporate carbon emissions remains underexplored in the literature. To address this gap, this study seeks to answer two key research questions: (1) How do rising corporate land prices affect carbon emission intensity? (2) Through what mechanisms—such as financing constraints or innovation reduction—do land prices influence emissions? By investigating these questions, we aim to provide a micro-level perspective that complements existing macro-level studies and sheds light on the nuanced ways in which land prices shape corporate environmental performance.

China is uniquely positioned as the research setting for this study for several reasons. First, China is the world's largest carbon emitter and has committed to ambitious climate goals, including carbon peaking by 2030 and carbon neutrality by 2060. These targets place immense pressure on policymakers and firms to address emissions, making it a critical context for studying carbon intensity determinants. Second, China's distinctive economic structure, characterized by state dominance and rapid urbanization, has led to significant variations in land prices across regions and industries, offering a rich setting to examine the heterogeneous impacts of land costs on corporate behavior. Third, land-based finance is a prevalent practice in China, where local governments rely heavily on land-related revenues for economic development. This reliance has driven land price inflation, which likely imposes financial constraints and innovation challenges on firms—mechanisms central to our study. Finally, China's institutional environment, including its centralized governance model and ongoing

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market reforms, provides a unique lens through which to explore land price dynamics and their environmental implications.

Our findings reveal that a 1% increase in corporate land prices leads to a 0.253% increase in carbon emission intensity, with results remaining robust across various sensitivity tests. To address potential endogeneity concerns, we employ instrumental variable techniques and a Difference-in-Differences (DID) model, both of which confirm the robustness of our findings. Furthermore, we explore the mechanisms through which land prices affect carbon emissions, finding that increased land prices raise financing constraints and reduce innovation, corroborating our theoretical hypotheses. Our heterogeneity analysis reveals that the impact of land prices on carbon intensity is more pronounced in central and western regions, in industries subject to stricter environmental regulations, in non-state-owned enterprises, and among firms that acquire land through public bidding.

This study makes several key contributions to the literature. First, it enriches the understanding of land price dynamics and their effect on carbon emissions at the micro level, complementing existing macro-level studies that focus on regional or national perspectives. Second, it broadens the scope of research on factors influencing carbon emissions, introducing micro-level land prices as a significant determinant. Third, by investigating the mechanisms of financing constraints and innovation, the study contributes to a deeper understanding of how land prices influence corporate behavior in terms of carbon emissions.

The remainder of this paper is structured as follows: Section "[Relative literature](#)" reviews the relevant literature; Section "[Theoretical hypotheses](#)" presents the theoretical hypotheses; Section "[Empirical design](#)" describes the research design, including data sources, econometric models, and variable definitions; Section "[Results and discussion](#)" presents the empirical results; and Section "[Conclusion](#)" concludes with policy recommendations.

Relative literature

The impact of land prices on firm behavior

This section focuses on how land prices influence corporate decisions and operational efficiency. Studies have shown that land prices affect firms by altering their cost structures and resource allocation. For example, high land prices have been linked to reduced labor productivity⁴, overcapacity⁵, and hindered industrial upgrading⁶. Land-based finance, a prevalent practice in China, exacerbates these challenges as it incentivizes local governments to prioritize land sales for revenue generation, distorting market dynamics and affecting firms' production decisions^{7,8}. Additionally, firms acquiring land through competitive bidding processes face higher operational costs, which can constrain their ability to invest in innovation or sustainability initiatives⁹.

Financing constraints and their role in emission dynamics

Rising land prices also exacerbate financing constraints for firms, limiting their ability to fund environmentally friendly initiatives or adopt innovative technologies. Existing literature highlights that financial constraints often lead firms to cut R&D spending and rely on cheaper, carbon-intensive energy sources¹⁰. For instance, firms under financial pressure are less likely to invest in renewable energy or energy-efficient technologies, directly increasing their carbon emission intensity¹¹. Furthermore, financing constraints disproportionately affect non-state-owned enterprises (SOEs), as SOEs often have better access to credit due to government backing¹². This dynamic underscores the importance of addressing financial barriers to enable firms to meet carbon reduction targets.

Innovation and emission reduction

Innovation plays a pivotal role in mitigating carbon emissions, and its relationship with land prices warrants attention. Studies show that rising land prices can stifle corporate innovation by reallocating resources away from R&D toward operational costs⁶. Firms in regions with higher land prices are less likely to develop low-carbon technologies or improve energy efficiency, exacerbating their carbon emission intensity^{13,14}. However, innovation also depends on external factors such as government R&D subsidies and intellectual property protection, which can counterbalance the adverse effects of land prices¹⁵.

Political influence on firms in China

Political influence in China profoundly shapes firm behavior and market dynamics, particularly under authoritarian capitalism. The Xi Jinping regime has strengthened state control through mandatory CSR reporting and policy-driven markets¹⁶. SOEs, as both profit-driven entities and extensions of state policy, face pressures to align with national objectives, increasing CSR engagement but also operational costs and regulatory burdens¹⁷. Politically connected firms gain financial stability through favorable policies but may sacrifice transparency, with CSR often serving symbolic purposes¹⁸. Private firms incur lobbying costs and strategic dependencies to align with state priorities, heightening financial constraints¹⁹. In carbon markets, established through pilot programs in 2013 and a national market in 2021, state influence drives trading and price stability. Economic policy uncertainty (EPU) exerts asymmetric effects on carbon prices, reflecting market sensitivity to state policies^{20,21}. Regional disparities in development and energy dependency amplify these effects, with some regions showing resilience to policy risks while others remain vulnerable²². Firms must navigate these challenges by balancing compliance with national objectives and managing uncertainties in policy-driven markets.

Research gaps and contributions

While the existing literature provides a rich theoretical framework and empirical evidence on the factors and mechanisms by which land-based finance influences carbon emissions, certain limitations persist. Most studies focus on macro-level analyses, primarily discussing the impact of land-based finance on carbon emissions at the

provincial level. However, as key contributors to carbon emissions, enterprises exhibit significant heterogeneity in how land-based finance affects them. Moreover, many studies directly examine the causal relationship between land-based finance and carbon emissions but lack comprehensive, systematic analyses of the mechanisms from the perspective of corporate decision-making.

Our study addresses these gaps by empirically analyzing the spatial effects and heterogeneity of land prices on carbon emissions from a micro-level perspective. We explore how rising land prices influence corporate carbon emission intensity through mechanisms such as heightened financing constraints and reduced innovation. This approach deepens the understanding of the relationship between land prices and carbon emissions, offering new insights into the micro-level effects of land factors on environmental outcomes.

Benefits and limitations

The benefits of our study include providing actionable insights for policymakers aiming to balance economic development with environmental sustainability, particularly in the context of land market reforms and corporate financing strategies. By integrating multiple micro-level databases, our study ensures a robust and detailed analysis, enhancing the reliability of the results.

This study acknowledges several limitations that must be addressed. First, the data span from 2000 to 2014, which, while offering valuable insights, fails to capture more recent dynamics in the relationship between land prices and corporate carbon emissions, particularly given the significant changes in policies and technologies in recent years. Second, the sample focuses exclusively on Chinese industrial enterprises, limiting the generalizability of the findings to other countries or sectors, particularly those outside the industrial domain or with distinct land market structures. Third, despite the inclusion of various control variables, omitted variable bias remains a concern, as factors such as policy changes, macroeconomic fluctuations, and regional differences in regulatory enforcement were not fully accounted for. Fourth, although instrumental variable (IV) and difference-in-differences (DID) methods were employed to address endogeneity, these approaches cannot completely eliminate all potential biases. Finally, the study uses patent applications as a proxy for corporate innovation, which may not fully reflect the breadth of innovation activities, particularly those related to process improvements or non-patentable advancements. Together, these limitations suggest avenues for refinement in future research.

Theoretical hypotheses

Financing constraint effects

For enterprises, land is a critical production factor, and rising land prices can lead to greater financial constraints. This study draws on the financial constraint theory to explain how rising land prices impact corporate behavior and carbon emissions. Financial constraint theory suggests that limited access to external financing can affect firms' decision-making processes, particularly their investments in technology and resource allocation.

Wan et al.¹⁰ found that financial factors can influence firms' use of fossil fuels, thereby increasing carbon emission intensity. Specifically, when financing constraints increase, firms are motivated to cut other costs in the following ways: First, they may resort to using cheaper energy sources. Industrial enterprises tend to use cheaper fossil fuels, which lead to higher carbon emissions²³. Moreover, the use of cheaper energy can affect a firm's energy input structure, and the significant relationship between energy structure and carbon emission intensity has been previously demonstrated¹¹.

Second, firms may reduce their research and development (R&D) expenditures. According to financial constraint theory, the financing constraint effect increases uncertainty for enterprises, causing them to delay long-term and high-risk R&D investments in an attempt to recover costs in the short term. The conclusion that uncertainty delays corporate R&D investment has been well-established in the literature²⁴. Furthermore, given the higher capital returns in the real estate market, banks are more inclined to increase loans to real estate firms to secure higher returns, which incentivizes firms to invest more in real estate, crowding out R&D investments¹². The significant relationship between R&D investment and carbon emission intensity has been confirmed by Lee and Min¹⁵.

Based on the financial constraint theory and the findings from existing literature, the following hypothesis is proposed:

Hypothesis 1 Rising land prices increase carbon emission intensity by exacerbating corporate financing constraints.

Innovation effect

The impact of rising land prices on corporate innovation behavior can take two directions. This study draws on agglomeration theory and financial constraint theory to explain the dual effects of rising land prices on corporate innovation and carbon emissions.

First, production agglomeration promotes innovation. Land prices reflect land value, and high land values indicate a high degree of agglomeration, including both production and population concentration. According to agglomeration theory, production agglomeration implies the concentration of talent and technology, and the spillover effects of such agglomeration can foster innovation within firms²⁵ as well as the diffusion of technology between firms, thereby helping to improve productivity and energy efficiency²⁶.

Second, reduced R&D investment suppresses innovation. As previously discussed in the context of the financial constraint effect, rising land prices can lead to a reduction in R&D expenditures. According to financial constraint theory, reduced R&D investment significantly hinders corporate innovation, as confirmed by numerous empirical studies⁶. Technological innovation is a key driver of carbon reduction, as it can optimize the

energy structure through the development of renewable resources²⁷, improve energy efficiency¹⁴, and promote the low-carbon transformation of production methods¹³, thereby reducing carbon emission intensity.

Based on the agglomeration theory and financial constraint theory, the following hypothesis is proposed:

Hypothesis 2 Land prices affect carbon emission intensity by influencing corporate innovation levels, but the direction of the effect is uncertain.

In summary, based on the above theoretical analysis, the impact of land prices on carbon emission intensity is uncertain. The theoretical analysis alone does not lead to a definitive conclusion, and further empirical testing is needed to determine the nature of the relationship between land prices and carbon emission intensity.

Empirical design

Data source

Our study is grounded in the theoretical framework that examines the relationship between land prices and corporate carbon emission intensity. We posit that rising land prices can lead to increased carbon emissions through two primary mechanisms: heightened financing constraints and reduced innovation. This hypothesis is informed by existing literature that explores the impact of financial constraints on corporate environmental performance and the role of innovation in mitigating carbon emissions.

To empirically test our hypotheses, we constructed a comprehensive dataset by integrating multiple micro-level databases: (1) Annual Survey of Industrial Firms (ASIF): Provided by the National Bureau of Statistics of China, ASIF encompasses all state-owned industrial enterprises and non-state-owned industrial enterprises above a designated scale. Industrial enterprises are categorized under mining, manufacturing, and the production and supply of electricity, gas, and water, with manufacturing constituting over 90% of the dataset. ASIF offers comprehensive insights into the operational status of Chinese industrial firms and is extensively utilized in academic research. (2) Pollution of Industrial Firms Database (PIFD): Released by the Ministry of Ecology and Environment of China, PIFD provides pollution emission data for state-owned and large-scale non-state-owned industrial enterprises. It includes detailed information on 27 industrial pollutants, such as solid waste, gas emissions, water pollution, and pollution control indicators, covering the period from 1998 to 2014. This database is the most comprehensive source of micro-level firm data on energy inputs and pollution emissions. (3) China Land Transaction Database: Sourced from the China Land Market website, this database records detailed information on land transactions across various regions in China, including specifics about enterprises (the land use right holders) purchasing land. (4) Global Carbon Dioxide Emissions Database: Obtained from the Center for Global Environmental Research (CGER) website, this database provides global CO₂ emission grid data from January 2000 to December 2019. (5) China Patent Database: Provided by the National Intellectual Property Administration, this database offers detailed information on patent applications by enterprises.

Using information such as legal entity codes, company names, phone numbers, postal codes, and geographic locations, we matched the five micro-level enterprise databases. The matching process was crucial to ensure consistency and accuracy across different data sources, minimizing the risk of mismatches that could bias the analysis. Following the method of Brandt et al. (2012), we processed the matched database as follows: (1) deleted samples with missing data to ensure data completeness; (2) removed anomalies, such as debt-to-asset ratios greater than 1, employee numbers less than 0, and assets less than 0, to maintain data validity; (3) incorporated province-level macroeconomic data, primarily sourced from the National Bureau of Statistics, into the matched micro-level enterprise database. Incorporating macroeconomic data enabled us to control for regional economic variations that might affect firm behavior, adding an important contextual layer to our analysis. This rigorous data cleaning ensured that our dataset was robust and reliable for analysis. Ultimately, we obtained a unique unbalanced panel dataset covering the period from 2000 to 2014, with 12,739 observations. The unbalanced nature of the panel allowed us to include firms that entered or exited the sample during the study period, providing a more comprehensive view of the dynamics at play. To prevent the influence of outliers on the results, all continuous variables were winsorized at the top and bottom 1%. This approach mitigated the potential distortion caused by extreme values, ensuring that the results reflect the central trends in the data.

Econometric specification

To test the theoretical hypotheses, we refer to the methodology of Guo et al.²⁸ and construct the following two-way fixed effects econometric model in Eq. (1). The two-way fixed effects model allows us to control for both time-invariant characteristics of each firm and common shocks across all firms over time. Specifically, it accounts for unobserved heterogeneity across firms and years, helping to isolate the impact of the key independent variables on the dependent variable. We include both firm fixed effects, which capture time-invariant characteristics unique to each firm, and time fixed effects, which control for factors that vary across time but are constant across firms. This approach helps mitigate omitted variable bias and provides a robust estimation of the relationships between land prices, corporate innovation, and carbon emission intensity.

$$CEI_{it} = \beta_0 + \beta_1 Price_{it} + X'_{it}\theta + \gamma_t + \delta_i + \varepsilon_{it} \quad (1)$$

where CEI_{it} represents the carbon emission intensity of firm i in year t ; $Price_{it}$ represents the average land price acquired by the firm; $X'_{it}\theta$ represents a series of control variables at the firm and provincial levels; γ_t represents the time fixed effect; δ_i represents the firm fixed effect; ε_{it} represents the error term. The coefficient of interest is β_1 , which is to estimate the magnitude of the effect of land price changes on carbon emission intensity.

Definition of variables

Dependent variable (CEI)

Following the approach of He et al.²⁹, we use “carbon emission intensity = CO₂ emissions/firm value added” as the dependent variable. This treatment has the advantage of eliminating differences in firm size. Regarding CO₂ emissions, since China does not mandate companies to disclose carbon emission information, few companies voluntarily report such data in their annual reports. Moreover, firms that are typically those excelling in emission control are more likely to disclose carbon emission data, making the availability of such data quite limited³⁰. Therefore, emission estimates become necessary. Referring to the methodology of Yu et al.³¹, we estimate a firm's carbon emissions using the formula: “industry carbon emissions * (firm operating costs/industry operating costs)”. The total industry carbon emissions data is obtained from the Carbon Emission Accounts & Datasets (CEADS) database, and the specific calculations follow the methods outlined in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. These calculations are based on the product of the consumption of various energy sources and their corresponding carbon emission factors.

Firm operating costs are measured using the “cost of goods sold” from the ASIF database, as operating costs refer to the cost incurred by firms in selling goods or providing services. This measure ensures consistency and comparability across firms by focusing on direct production costs, which are closely related to firms' operational efficiency. Industry operating costs are calculated by summing the operating costs of all firms within the industry. This aggregation captures the overall cost structure of the industry, providing a basis for estimating individual firms' share of total industry emissions. For ease of interpretation, we take the logarithm of carbon emission intensity, resulting in the dependent variable, CEI, which is used throughout this paper. The logarithmic transformation helps normalize the distribution of the variable, reducing skewness and making the results more robust to extreme values.

Independent variable (price)

The core explanatory variable in this paper is the land price at the firm level, which is calculated as “the transaction price of land acquired by the firm/total land area”. This measure provides a firm-specific cost perspective, allowing us to capture variations in land expenses that directly impact firms' financial decisions. Both data points are sourced from the China Land Market website, ensuring the reliability and accuracy of the land price data. We scraped the relevant information on firm land purchases from the website and merged it with the ASIF database, thus obtaining micro-level data on firms' land assets. This integration allowed us to create a comprehensive dataset that combines land acquisition details with firm-level characteristics, providing a rich context for analysis. Following the methodology of Yan and Sun⁹, if a firm acquires multiple plots of land in a given year, we use the average transaction price of all land purchases. This approach standardizes the land price measure across firms and reduces the potential impact of outlier transactions. For ease of interpretation, we also take the logarithm of the land price, resulting in the core explanatory variable, referred to as Price. The logarithmic transformation helps normalize the distribution, making it more suitable for regression analysis and reducing the influence of extreme values. Figure 1 illustrates the distribution of firms and the land prices they paid in 2014, providing a visual representation of regional disparities in land costs. It is evident that firms in the eastern coastal regions tend to face higher land transaction prices, while firms in the central regions generally encounter land prices around the median or lower. This regional variation reflects differences in economic development, demand for land, and government policies across regions. In contrast, firms in the western regions tend to face significantly lower land prices, which may indicate lower economic activity and demand for land in these areas.

Control variables

Following Wang et al.³², both firm-level and regional-level control variables are included in the analysis. This selection helps to account for the different factors that may influence carbon emission intensity at both the micro (firm) and macro (regional) levels, thus providing a more comprehensive analysis. The firm-level control variables consist of: firm age (Age), firm size (Size), leverage ratio (Lev), profit margin (Profit), and ownership type (Soe). These variables are crucial in capturing the internal characteristics and financial health of firms, which can significantly impact their emission behaviors. The regional-level control variables include: regional economic growth rate (GdpRate), proportion of the secondary industry (Structure), population growth rate (PopGrowth), foreign direct investment (Fdi), and government fiscal pressure (FisPressure). These variables help capture the broader economic and policy environment, which can shape firms' environmental performance. The rationale for selecting these control variables is as follows: Firm-level and regional-level factors can collectively shape firm behavior, influencing both innovation activities and environmental outcomes. By including these variables, we aim to control for potential confounding factors that could bias our results. The firm-level control variables are commonly used and represent key firm characteristics. Firm age is controlled for because firms at different stages of growth may have different business objectives and strategies, which could influence their carbon emission intensity. Firm size has been shown to affect performance³³, ESG scores³⁴, and carbon emission intensity³¹. Larger firms may have more resources to invest in emission reduction technologies, while smaller firms may face more constraints in this regard. Similarly, leverage ratio and profit margin, as important indicators of firm performance, have been found to be closely related to a firm's emission behavior. Higher leverage may limit a firm's ability to invest in green technologies due to financial constraints, while higher profit margins may enable more investment in sustainability initiatives. However, the direction of this correlation is not always consistent, as financial constraints and strategic priorities may vary across firms and industries. On the one hand, reducing pollution can be a cost burden for firms, potentially harming their competitiveness, especially in industries where margins are already tight. On the other hand, emission reduction can improve efficiency and lower costs,

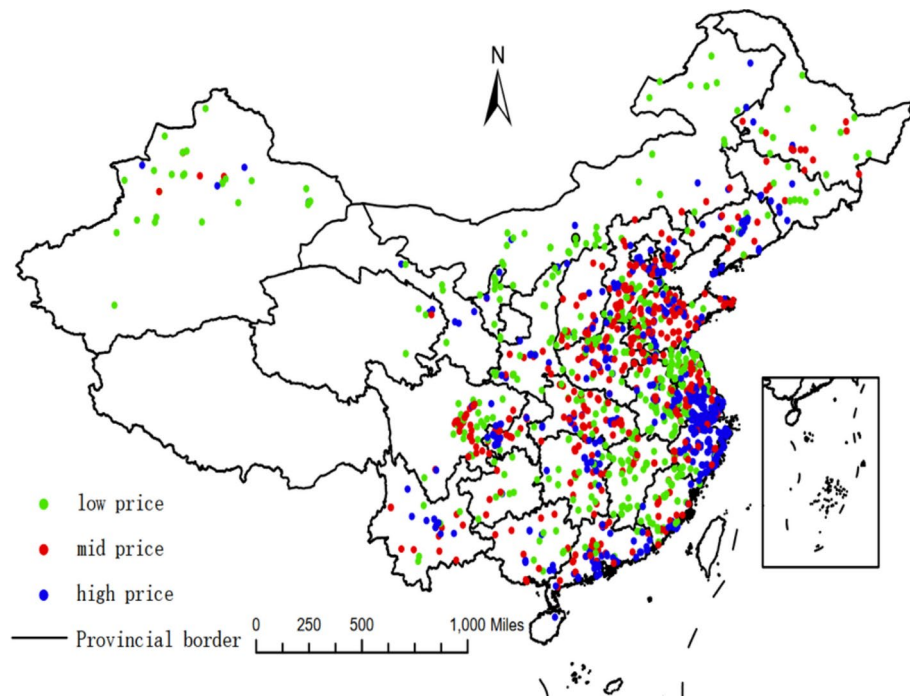


Fig. 1. The distribution of firm land price (2014). *Notes:* Plotted by the author. The price of land is categorized into three equal parts, defined as low-price, mid-price, and high-price. The map was generated using ArcGIS 10.1 (Esri, <https://www.esri.com/en-us/arcgis>).

giving firms a competitive cost advantage³⁵. Additionally, firms that successfully reduce emissions may benefit from an enhanced reputation and stronger relationships with environmentally conscious stakeholders.

Regional-level economic development also influences carbon emissions, playing a critical role in shaping emission patterns at both macro and micro scales. Azomahou et al.³⁶ found a significant and stable correlation between carbon emission intensity (per capita) and GDP per capita, indicating that economic growth is often accompanied by increased emissions, especially in earlier stages of development. Waheed et al.³⁷ presented a comprehensive literature review on the relationship between economic growth and carbon emissions, highlighting the complexity of this relationship across different countries and stages of economic development. Some studies show an inverted U-shaped relationship (i.e., the Environmental Kuznets Curve hypothesis), suggesting emissions rise initially with economic growth but eventually decline, others find a consistently positive correlation, while some indicate no significant relationship between the two, depending on contextual factors such as energy policies and industrialization levels. Moreover, economic development is not merely reflected in growth rates—industrial structure plays a crucial role in determining the sustainability of that growth. The composition of industries within a country or region directly impacts energy consumption patterns and carbon emissions. Industrial sectors, particularly heavy manufacturing, require substantial energy inputs, often derived from fossil fuels, resulting in higher carbon emissions. This makes industrial restructuring an essential component of reducing carbon footprints. In fact, changes in industrial structure, such as a shift from manufacturing to services, have been demonstrated to be a key factor influencing China's carbon emissions³⁸, highlighting the potential of structural shifts in achieving emission reduction goals. Population growth has also been empirically shown to impact carbon emissions³⁹, as an increasing population generally leads to higher energy demand and greater resource consumption. The relationship between foreign direct investment (FDI) and environmental quality has been extensively studied, with mixed results reflecting the diverse nature of FDI flows and host country policies. Eskeland and Harrison⁴⁰ reported that foreign firms tend to use more efficient and cleaner technologies, suggesting a positive environmental impact of FDI. In contrast, Paziienza⁴¹ identified a negative relationship between FDI and air pollution, indicating that without stringent environmental regulations, FDI can exacerbate pollution. On the other hand, Acharyya⁴² found a positive correlation between FDI and air pollution, supporting the 'pollution haven' hypothesis, which suggests that multinational corporations may relocate to countries with lax environmental regulations to minimize compliance costs. Additionally, higher government fiscal pressure may prompt governments to prioritize short-term economic growth over long-term environmental protection, potentially leading to weakened environmental policies and increased emissions. The main variables and definitions used in this study are summarized in Table 1.

Descriptive statistics

Table 2 presents the descriptive statistics for the key variables in this study. The mean value of carbon emission intensity (CEI) is 1.72, with a standard deviation of 0.986. The logarithmic value of carbon emissions was estimated at approximately 5.4, which is fairly close to the value of 3.058 derived by Pan and Wang³⁰ using data

Variable		Definition
Dependent var		
CEI	Carbon emission intensity	Log(1 + Carbon emission/Value added)
Explanatory var		
Price	Price of land	Log(1 + Total price/ Total land supply)
Firm controls		
Age	Age of firm	Log(1 + Years of operation since the establishment)
Size	Size of firm	Log(1 + Total asset)
Lev	Asset-liability ratio	Total asset /Total liability
Profit	Profitability	Total Profit/Total asset
Soe	Ownership	SOE = 1, non-SOE = 0
Region controls		
Gdp	GDP per capita	Log(1 + GDP per capita)
Growth	Development growth	GDP growth rate
Structure	Industry structure	Value added in the secondary industry/value added in the tertiary industry
PopGrowth	Population growth	population growth rate
Fdi	Foreign direct investment	FDI/ GDP
FisPressure	Fiscal pressure	General budget expenditure/general budget income

Table 1. The definition of variables.

Variable	Obs	Mean	Std. Dev	Min	Max
CEI	12,739	1.72	0.986	0.017	7.267
Price	12,739	5.14	0.959	0	11.002
Age	12,739	2.218	1.282	0	4.428
Size	12,739	12.352	1.767	8.618	16.975
Lev	12,739	0.404	0.181	0.017	0.868
Profit	12,739	0.117	0.182	-0.126	0.959
Soe	12,739	0.151	0.358	0	1
Gdp	12,739	10.436	0.437	9.354	11.268
Growth	12,739	0.142	0.057	0.026	0.259
Structure	12,739	1.199	0.217	0.697	1.783
Popgrowth	12,739	0.038	0.022	0	0.077
Fdi	12,739	0.033	0.019	0	0.067
FisPressure	12,739	1.913	0.6	1.118	3.958

Table 2. The summary statistics. Statistics by the author. CEI represents Carbon Emission Intensity; Price denotes the Price of Land; Age indicates the Age of the Firm; Size refers to the Firm Size; Lev stands for the Asset-Liability Ratio; Profit represents Profitability; Soe indicates Ownership Type; Gdp corresponds to GDP per Capita; Growth denotes Development Growth; Structure reflects the Industry Structure; PopGrowth represents Population Growth; Fdi stands for Foreign Direct Investment; and FisPressure indicates Fiscal Pressure.

from publicly listed companies. The mean value of land price (Price) is 5.14, with a standard deviation of 0.959, which aligns with the estimates provided by Yan and Sun⁹. Other variables are not discussed further in this section.

Results and discussion
Baseline regression

This section empirically examines the causal relationship between firm land prices and carbon emission intensity. Before conducting formal tests, we first examine the correlation between these variables. Figure 2 visually demonstrates that as firm land prices (Price) increase, carbon emission intensity (CEI) also shows an upward trend, indicating a positive relationship between the two variables.

Next, we perform a rigorous empirical test using the two-way fixed effects econometric model (1), employing a stepwise regression approach. The detailed results are presented in Table 3. Column (1) presents results from a simple OLS regression. The coefficient for Price is 0.121, statistically significant at the 1% level, indicating that a 1% increase in firm land prices leads to a 0.121% increase in carbon emission intensity. Column (2) reports the results using robust standard errors to address potential heteroscedasticity. The coefficient remains unchanged

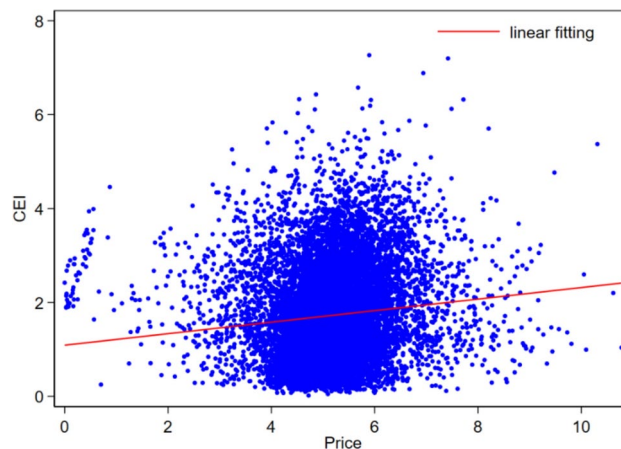


Fig. 2. The connection between Price and CEI.

despite a slight increase in standard errors. In Column (3), when additional control variables are included, the coefficient for Price increases to 0.234 and remains significant at the 1% level, indicating that a 1% increase in firm land prices leads to a 0.234% increase in carbon emission intensity. Column (4) adds both firm and time fixed effects. The coefficient for Price is 0.253, and it remains significant, indicating that a 1% increase in firm land prices leads to a 0.253% increase in carbon emission intensity. We consider the results in Column (4) as the benchmark. The key finding here is that rising firm land prices consistently and significantly increase carbon emission intensity, even after controlling for various factors and applying robustness checks.

Focusing on the policy implications, our results suggest that rising land prices, driven by economic development and urban expansion, could significantly hinder carbon reduction efforts by increasing firms' carbon emission intensity. This is particularly relevant as urban areas continue to expand, and firm land prices are likely to rise further. Policymakers should implement stricter land use regulations and incentivize the adoption of green technologies to mitigate the negative impact of rising land prices on emissions. Specifically, policies that encourage firms to adopt energy-efficient technologies and practices could help counteract the emission-increasing effects of rising land prices. Additionally, firm-level characteristics such as firm size (Size), industrial structure (Structure), and fiscal pressure (FisPressure) are found to significantly increase carbon emission intensity, highlighting the need for targeted interventions at the firm level. These findings underscore the importance of a dual-pronged policy approach: addressing both land pricing mechanisms and firm characteristics to effectively control emissions and promote sustainable development.

Our findings are consistent with the existing literature on the impact of land prices on firm behavior, while also providing novel insights at the micro-level. For instance, Gai et al.⁴, Han and Huang⁶ demonstrated that high land prices negatively affect labor productivity and hinder industrial upgrading, and our study extends these findings by showing a direct link between increased land costs and higher carbon emission intensity. Shen and Huang⁴³ examined the correlation between rising land prices and increased emissions in terms of energy consumption intensity, while our study offers a more comprehensive analysis of carbon emission intensity, incorporating robustness checks to enhance understanding of the environmental consequences of rising land costs. Similarly, Doğan et al.^{2,3} emphasized that economic complexity and structural transformation play critical roles in mitigating environmental degradation, suggesting that firms under financial pressure due to increased land costs are less likely to invest in sophisticated, low-carbon technologies. Our findings further align with those of Xu et al.⁴⁴, who indicated that increased production costs in energy procurement lead firms to maximize output, thus driving up emissions—similar to how rising land prices push firms to increase production. Overall, our results highlight the micro-level impacts of land costs on environmental outcomes, complementing macro-level studies such as those by Fernando and Hor¹ that stress the global importance of carbon reduction.

The positive association between land prices and carbon emission intensity can be explained through multiple theoretical perspectives. Firstly, Cost-Push Theory posits that higher land prices increase production costs, compelling firms to intensify production activities to sustain profitability, resulting in higher emissions due to more energy-intensive processes^{6,11}. Secondly, Urban Expansion Theory explains that as cities expand and land becomes increasingly scarce, firms are forced to either relocate or maximize output from limited land, leading to greater emissions^{8,10}. The Environmental Kuznets Curve (EKC Hypothesis also partially supports our findings, suggesting that economic growth initially exacerbates environmental degradation until a certain income level is reached, after which environmental quality improves, rising land prices can be seen as a byproduct of such growth, driving emissions upward until effective regulatory or technological interventions are made³. Furthermore, Financing Constraint Theory indicates that rising land prices exacerbate financial constraints, limiting firms' ability to invest in eco-friendly initiatives or innovative technologies^{10,15}. This aligns with our findings that non-state-owned enterprises, which face greater financial challenges, are particularly vulnerable to the adverse effects of rising land prices¹². Lastly, Innovation Theory suggests that while production agglomeration can foster innovation, the financial burden from rising land costs often leads firms to cut back on R&D expenditures,

Variables	(1)	(2)	(3)	(4)
	CEI	CEI	CEI	CEI
Price	0.121*** (0.00904)	0.121*** (0.0103)	0.234*** (0.0101)	0.253*** (0.0313)
Age			−0.00926 (0.00563)	−0.00897 (0.0135)
Size			−0.0118*** (0.00451)	0.111* (0.0589)
Lev			0.0771* (0.0435)	−0.161 (0.193)
Profit			−0.0607 (0.0420)	0.0179 (0.189)
Soe			0.0122 (0.0212)	−0.0655 (0.117)
Gdp			−0.497*** (0.0311)	−0.496 (0.405)
Growth			1.671*** (0.154)	−2.171** (0.953)
Structure			−0.545*** (0.0392)	0.608** (0.237)
Popgrowth			−0.0648 (0.325)	0.0878 (0.786)
Fdi			0.0689 (0.373)	−0.204 (0.907)
FisPressure			0.535*** (0.0215)	0.555*** (0.215)
Firm FE	No	No	No	Yes
Year FE	No	No	No	Yes
Robust	No	Yes	Yes	Yes
Observations	12,742	12,742	12,739	12,739
R-squared	0.014	0.014	0.102	0.155

Table 3. Baseline regression. Firm FE represents firm fixed effects, Year FE represents year fixed effects, and Robust represents adopting clustered robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. CEI represents Carbon Emission Intensity ($\text{Log}(1 + \text{Carbon emission}/\text{Value added})$); Price denotes the Price of Land; Age indicates the Age of the Firm; Size refers to the Firm Size; Lev stands for the Asset-Liability Ratio; Profit represents Profitability; Soe indicates Ownership Type; Gdp corresponds to GDP per Capita; Growth denotes Development Growth; Structure reflects the Industry Structure; PopGrowth represents Population Growth; Fdi stands for Foreign Direct Investment; and FisPressure indicates Fiscal Pressure.

thereby reducing innovation and increasing carbon emission intensity^{6,13,25}. These theoretical perspectives collectively help to explain the mechanisms underlying our empirical findings.

Robustness test

To ensure the robustness of the basic regression results, this section performs a series of robustness checks, as shown in Table 4.

Replacing the dependent variable

Some scholars, such as Shen and Huang⁴³, use the ratio of “CO₂ emissions to main business revenue” to measure carbon emission intensity. Following their approach, this paper recalculates the dependent variable (CEI_revenue) accordingly. Results are presented in Column (1), where the coefficient for Price is 0.303, which is statistically significant at the 1% level. This indicates that rising land prices lead to higher carbon emission intensity even when different measurement approaches are used, reinforcing the robustness of our findings.

To ensure the reliability of the carbon emission intensity measurement, this paper also uses atmospheric CO₂ concentration within a 1 km radius around the firm as a proxy for carbon emissions (CEI_concentration) in the regression analysis. This approach is justified for the following reasons: (1) CO₂ emissions in the atmosphere can be directly monitored, eliminating the need for estimations and ensuring data reliability. (2) The concentration of CO₂ within a 1 km radius is predominantly influenced by the firm’s activities. (3) The stable portion of atmospheric CO₂ naturally present in the environment allows focus on the growth rate of carbon emission intensity, excluding the stable background portion. The calculation steps include: first, based on the firm’s location, creating a circular buffer zone with a 1 km radius around the firm. Second, CO₂ emission data

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CEI_revenue	CEI_concentration	CEI_energy	CEI	CEI	CEI
Price	0.303***	0.100***	0.187**	0.149***	0.216**	0.240***
	(0.0412)	(0.00159)	(0.0816)	(0.0463)	(0.0965)	(0.0239)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,729	12,731	445	5611	3215	12,742
R-squared	0.188	0.718	0.213	0.169	0.208	0.139

Table 4. Robustness. Firm FE represents firm fixed effects, Year FE represents year fixed effects, and Robust represents adopting clustered robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. CEI represents Carbon Emission Intensity (Log(1 + Carbon emission/Value added)), CEI_revenue represents carbon emission intensity measured using main business revenue; CEI_concentration denotes carbon emission intensity estimated based on the atmospheric CO₂ concentration within a 1 km radius around the firm; CEI_energy indicates carbon emission intensity calculated using energy input.

at a 1 km x 1 km resolution from the CGER is converted into raster data. Third, the raster data is extracted and clipped using the buffer zone to obtain carbon emission data within the 1 km radius around the firm. Results in Column (2) show that the coefficient for Price is 0.100, statistically significant at the 1% level, indicating a consistent positive effect of land prices on carbon emissions, which further supports the main conclusion that rising land prices elevate carbon intensity.

Some scholars estimate carbon emissions directly from firms’ energy inputs⁴⁴. Carbon emissions are calculated using Eq. (2):

$$CO_2 = \sum_{i=1}^8 E_i \times \beta_{co2, i} = \sum_{i=1}^8 E_i \times \left(NCV_i \times CC_i \times COF_i \times \frac{44}{12} \right) \tag{2}$$

where CO₂ represents carbon emissions, and E_i denotes the total energy consumption of energy source *i*, converted to standard coal equivalent. The specific calculation formula is: “actual energy consumption × standard coal conversion factor”. The variable *i* represents the eight major energy sources: coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. β_{co2, i} represents the carbon dioxide emission factor of energy source *i*, calculated in Eq. (3):

$$NCV_i \times CC_i \times COF_i \times \frac{44}{12} \cdot NCV_i \tag{3}$$

where NCV_i is the average low level heat generation of primary energy. CC_i is the carbon content of energy source *i*. COF_i is the carbon oxidation factor. 44 and 12 are the molecular weights of carbon dioxide and carbon, respectively. Since the energy consumption data provided by the PIFD includes coal, fuel oil, diesel, clean gas, coke, and natural gas, and given that data for coke and natural gas are severely missing, consumption data for the first four energy sources were used, with clean gas data converted using the natural gas conversion factor. Carbon emission intensity was recalculated (CEI_energy) for firms, and the regression was re-run. Results in Column (3) indicate that the coefficient for Price is 0.187 and statistically significant at the 5% level, again confirming that rising land prices are positively associated with carbon emission intensity, providing further robustness to our core findings.

Excluding border firms

Since corporate pollution emissions have negative externalities, firms in border regions incur lower social costs than the economic benefits derived from their production and pollution⁴⁵. Additionally, the decentralized nature of territorial-based environmental governance often results in a lack of communication and coordination between jurisdictions, leading to serious local protectionism. This creates enforcement vacuums and pollution hotspots in border regions⁴⁶, leading to higher pollution levels. Therefore, the presence of firms located in border regions may lead to an overestimation of the baseline regression results in this study. To address this issue, firms located near provincial borders were excluded, and the regression was re-run. Results presented in Column (4) indicate that the coefficient for Price is 0.149 and is statistically significant at the 1% level, suggesting that the positive effect of land prices on carbon emission intensity holds even when border firms are excluded, reducing potential biases from regional externalities.

Removing the impact of the carbon pilot policy

To meet greenhouse gas emission control targets, the National Development and Reform Commission (NDRC) implemented the Low-Carbon City Pilot Policy in 2010 and gradually expanded its scope. This policy mandates regions to set total greenhouse gas emission control targets, which directly impacts corporate carbon emission intensity. To exclude the potential effects of this policy, the sample period was shortened to 2000–2009. Results in Column (5) show that the coefficient for Price is 0.216 and statistically significant at the 5% level, indicating that even in the absence of policy interventions aimed at carbon reduction, rising land prices contribute significantly to increased carbon emission intensity. This further emphasizes the need for policy measures to counteract the emission-inducing effects of rising land costs.

Employing DK standard errors

To address potential issues of autocorrelation, heteroscedasticity, and cross-sectional dependence, the model was re-estimated using Driscoll and Kraay⁴⁷ standard errors (DK standard errors). Results in Column (6) indicate that the coefficient for Price is 0.240, and it remains statistically significant at the 1% level. This suggests a robust and consistent relationship between land prices and carbon emission intensity, reinforcing the reliability of our findings across different econometric specifications.

Further discussion

The empirical analysis above employed a two-way fixed effects model to identify causal relationships. Nonetheless, this causal identification strategy encounters potential endogeneity challenges. For example, rising land prices can increase carbon emission intensity, but higher carbon emissions may lead to stricter government regulations⁴⁸, which could make land acquisition more difficult and drive up land prices, representing a typical case of bidirectional causality. Additionally, measurement errors in land prices and endogeneity arising from unobserved factors could also lead to significant bias in the baseline regression coefficients. To address these potential endogeneity concerns, this section adopts two empirical strategies. Additionally, potential mechanisms through which land prices affect carbon emissions are examined. Detailed regression results are presented in Table 5.

Instrumental variable method

Following Yan and Sun⁹, the land price is instrumented by the land volume ratio. The land volume ratio is exogenous because it is determined by the government prior to the transaction, and it does not directly affect firms’ carbon emission intensity. Second, a stable and significantly positive relationship exists between the land volume ratio and land price. The measurement equation for the two-stage instrumental variable method is represented by Eqs. (4) and (5):

Stage 1 : $Price_{it} = \beta_0 + \beta_1 Volume_{it} + X' \theta + \gamma_t + \delta_i + \varepsilon_{it}$ (4)

Stage 2 : $CEI_{it} = \beta_0 + \beta_1 \widetilde{Price}_{it} + X' \theta + \gamma_t + \delta_i + \varepsilon_{it}$ (5)

The first stage regresses the instrument on the endogenous variable ($Price_{it}$) and all other control variables. A fitted value (\widetilde{Price}_{it}) is obtained, which removes the endogenous component of $Price_{it}$. In the second stage, carbon emission intensity is regressed on the fitted value to obtain the coefficient after accounting for

Variables	2SLS		CEI	Mechanisms	
	Price	CEI		Constraint	Innovation
	(1)	(2)	(3)	(4)	(5)
Price		0.340*** (0.0960)		0.0133*** (0.00275)	− 0.0907*** (0.00718)
Land#Post			0.0884*** (0.0255)		
Volume	0.942*** (0.186)				
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust	Yes	Yes	Yes	Yes	Yes
Observations	2741	2741	12,739	12,399	12,739
R-squared	0.160	0.161	0.091	0.493	0.096

Table 5. Results from 2SLS and Mechanism Analysis. The Kleiberg--Paap rk LM statistic is 33.498, which significantly rejects the null hypothesis of under-identification test. The hypothesis of weak instrumental variables is rejected, because Kleibergen–Paap rk Wald F statistic is 25.806. Firm FE represents firm fixed effects, Year FE represents year fixed effects, and Robust represents adopting clustered robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

endogeneity. Columns (1) and (2) of Table 5 show the results. In Column (1), the coefficient of *Volume* in the first stage is 0.942 and significant at the 1% level, indicating a strong instrument and justifying its use in addressing endogeneity concerns. In Column (2), the coefficient of *Price* in the second stage is 0.340 and significant at the 1% level, indicating that rising land prices still have a significant positive impact on carbon emission intensity after accounting for endogeneity. This strengthens the causal interpretation of our findings.

Land policy shocks

The Ministry of Finance, the Ministry of Land and Resources, the People's Bank of China, the Supervision Department, and the Auditing Administration issued a joint "Notice on Further Strengthening the Management of Land Transfer Revenue and Expenditure" (MLTRE). This policy requires that, beginning in 2010, all land transfer revenue be fully deposited into the local treasury, with expenditures arranged through the local fund budget based on land transfer income. Should local governments fail to pay land transfer revenue on time and in full, unlawfully reduce or delay payments, or covertly reduce land transfer revenue, they will be held administratively accountable. The MLTRE policy significantly restricts local governments' fiscal behavior related to land and reduces the supply of land to enterprises. This represents a notable external shock to land prices, providing a valuable quasi-natural experiment to identify the causal relationship between land prices and carbon emission intensity. Given that enterprises with higher land acquisition prior to the policy are more severely impacted, we follow the approach of Lu and Yu⁴⁹ and construct the following intensity DID Eq. (6):

$$CEI_{it} = \beta_0 + \beta_1 \text{Land}_{i,2000-2009} \times \text{Post}_{2010} + X_i' \theta + \gamma_t + \delta_i + \varepsilon_{it} \quad (6)$$

where Post_{2010} represents a dummy variable for the MLTRE policy shocks, assigned a value of 1 for 2010 and later years, and 0 for prior years; $\text{Land}_{i,2000-2009}$ represents the average land area purchased by firms prior to the MLTRE policy. Other variables remain as previously defined. β_1 is the coefficient of interest, measuring the effect of the MLTRE policy. Results are shown in Column (3), where the coefficient of $\text{Land} \times \text{Price}$ is 0.0884 and significant at the 1% level, indicating that the MLTRE policy-induced increase in land prices significantly contributes to higher carbon emission intensity, consistent with our baseline results.

The intensity DID model requires that the experimental and control groups meet the parallel trends assumption. To verify this assumption, an event study method is employed to conduct a dynamic test. The econometric equation is defined in Eq. (7):

$$CEI_{it} = \beta_0 + \sum_{\delta=-4}^{+4} \beta^\delta \text{Land}_{i,2000-2009} \times \text{Post}^\delta + X_i' \theta + \gamma_t + \delta_i + \varepsilon_{it} \quad (7)$$

where δ represents the event. When the policy occurs, $\delta=0$; one period before, $\delta=-1$; one period after, $\delta=+1$; and so on for other periods. Figure 3 shows that the coefficients are not significant at the 95% level for events before 0, indicating no pre-existing differences between the treatment and control groups, thus satisfying the parallel trends assumption. For periods where the event is greater than 0, the coefficients are statistically significant and positive, suggesting that the MLTRE policy shock had a sustained effect on increasing corporate carbon emission intensity.

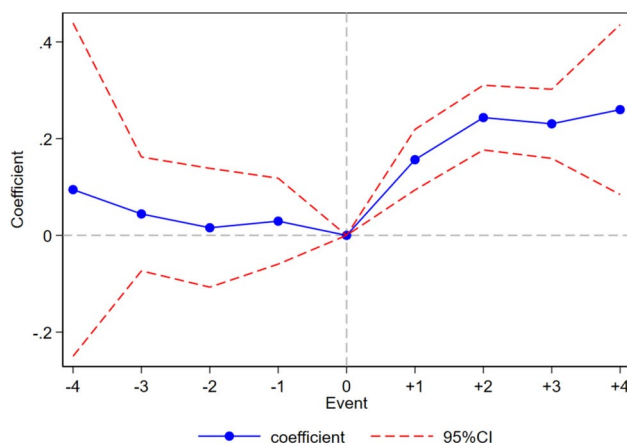


Fig. 3. Dynamic analysis. *Notes:* The baseline time is the period when Event = 0.

Variables	Region		Transfer		Ownership		Regulation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	East	West & Central	Aggrement	BAL	Soe	Non-Soe	High	Low
Price1	0.173** (0.0709)	0.278*** (0.0505)	0.227*** (0.0851)	0.323*** (0.0452)	0.119* (0.0693)	0.297*** (0.0362)	0.153*** (0.0461)	0.329*** (0.0581)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Y
Observations	4606	8133	2488	10,251	1922	10,817	5573	7166
R-squared	0.314	0.159	0.391	0.161	0.137	0.173	0.140	0.213

Table 6. Heterogeneity analysis. Firm FE represents firm fixed effects, Year FE represents year fixed effects, and Robust represents adopting clustered robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Mechanism analysis

This section empirically tests the mechanism hypotheses discussed earlier to validate the theoretical analysis. The specific results are presented in Table 5. Column (4) examines the effect of financing constraints. The hypothesis posits that rising land prices exacerbate corporate financing constraints. Following Yan and Sun⁹, the ratio of "current liabilities to total assets" is used to measure a firm's financing constraints, with higher values indicating greater constraints. The results show that the coefficient for Price is 0.0133 and statistically significant at the 1% level, indicating that higher land prices significantly exacerbate firms' financing constraints, aligning with expectations. In recent years, Chinese local government financing vehicles (LGFVs) have played a pivotal role in funding infrastructure projects, actively engaging in land development, affordable housing construction, and other initiatives. However, with the continuous rise in land prices, these enterprises face increasingly severe financing constraints. The escalating cost of land has significantly heightened their capital requirements, compelling them to seek additional external financing. At the same time, regulatory measures on land financing activities—such as the prohibition of using reserved land as assets for financing platform companies—have further restricted their financing channels. Together, these factors have led to a substantial increase in financing difficulty and costs in high land-price environments, thereby limiting the expansion of their operations and the development of their projects (<https://finance.sina.com.cn/roll/2024-06-26/doc-inazzwmm6237166.shtml>).

Column (5) examines the effect of innovation. The hypothesis suggests that the impact of land prices on a firm's innovation level is uncertain. As patent applications are a reliable and timely indicator of a firm's innovation capability⁵⁰, the number of patent applications is used to measure innovation level. Patent data were sourced from the China National Intellectual Property Administration's patent application database and matched with ASIF following He et al.⁵¹. Results show that the coefficient for Price is -0.0907 and statistically significant at the 1% level, indicating that higher land prices significantly suppress a firm's innovation level. In recent years, the negative impact of rapidly rising land prices on corporate innovation has become increasingly evident. According to a report by the Daily Economic News, the average sale price of residential housing in China increased by 6.37 times from 2004 to 2016, far outpacing the growth in household incomes over the same period. This phenomenon has led to a significant crowding-out effect: studies indicate that during periods of sharp increases in housing prices, firms have redirected their financial resources toward land acquisition and real estate development, rather than investing in high-cost, high-risk, but long-term innovation endeavors. Research from the Tsinghua University Hang Lung Center for Real Estate further highlights that listed companies generally reduced their R&D expenditures during periods of rising housing prices, reallocating resources to the real estate sector. This illustrates how high housing prices substantially encroach upon firms' innovation investments. Additionally, rising housing prices have caused resource misallocation, diverting capital from high-efficiency sectors to lower-productivity industries such as real estate and its related fields, further suppressing overall economic growth and technological advancement. These real-world examples and data strongly support the findings of this study: rising land prices exacerbate corporate financing constraints and resource misallocation, thereby significantly hindering firms' innovation activities (<https://www.nbd.com.cn/articles/2018-08-22/1247792.html>).

Heterogeneity analysis

To deepen the understanding of the impact of firm land prices on carbon emission intensity, a series of heterogeneity analyses were conducted to observe differences in land price effects across various contexts. The detailed regression results are presented in Table 6.

Enterprise location

China exhibits significant regional disparities in development, particularly in economic growth, institutional environments, and local government bargaining power across the eastern, central, and western regions⁵². These differences result in significant regional heterogeneity in the impact of land factors on environmental performance⁵³. The central and western regions, as noted by Wang et al.³², have lower economic development levels, a concentration of energy-intensive industries, and limited green technology innovation compared to the eastern region. Governments and enterprises in these regions are more likely to prioritize profits over environmental protection. Therefore, the impact of land prices on carbon emission intensity is expected to be

stronger in the central and western regions. Based on the regional classification standards of the National Bureau of Statistics, the sample was divided into two sub-samples: eastern and central-western regions, followed by separate regressions. Columns (1) and (2) indicate that the coefficient for Price is higher in the central-western region ($0.278 > 0.173$), which aligns with expectations.

The method of land transfer

In China, two primary methods of land transfer exist: negotiated agreements and public bidding (auction or listing). Yan and Sun⁹ note that land prices are generally lower under negotiated agreements compared to public bidding. Thus, the impact of land prices on carbon emission intensity is expected to be lower in firms acquiring land through negotiated agreements. Based on land transfer method data from the China Land Transaction Database, the sample was divided into two sub-samples: negotiated agreements and public bidding, followed by separate regressions. Columns (3) and (4) indicate that the coefficient for Price is larger for the public bidding method ($0.323 > 0.227$), consistent with expectations.

The ownership of the enterprise

State-owned enterprises (SOEs) serve as pillars of the national economy in China. Due to their strategic positions and close relationships with the government, SOEs are more likely to receive policy incentives and support⁵⁴. As a result, SOEs face soft budget constraints, meaning their decision-making is less influenced by land prices⁹. Thus, the impact of land prices on carbon emission intensity is expected to be lower for SOEs. Based on firm registration types from the ASIF database, the sample was divided into SOEs and non-SOEs, followed by separate regressions. Columns (5) and (6) indicate that the coefficient for Price is larger in non-SOEs ($0.297 > 0.119$), aligning with expectations. This result is consistent with conclusions on land acquisition methods, as SOEs, due to their close ties with government departments, often acquire land at lower prices through negotiated agreements.

The intensity of environmental regulation.

Firms in regions with higher levels of environmental regulation are subject to stricter oversight and stronger penalties⁵⁵. As a result, firms in these regions have stronger incentives to improve their environmental performance⁵⁶. Thus, the impact of land prices on carbon emission intensity is expected to be stronger in regions with lower environmental regulation. This study used “three wastes” emissions data from each province, applying the entropy method to calculate a comprehensive environmental regulation index. Firms were divided into two sub-samples: high and low environmental regulation, based on the index’s median value. Grouped regressions were conducted accordingly. Columns (7) and (8) indicate that the coefficient for Price is larger in regions with low environmental regulation ($0.329 > 0.153$), aligning with expectations.

Conclusion

China, as a leading global carbon emitter, has set ambitious goals for carbon peaking and neutrality. This study offers a pioneering analysis of how micro-level land prices affect corporate carbon emission intensity, providing new insights into the environmental impact of land factors. Our findings indicate that rising land prices significantly increase carbon emissions through two primary mechanisms: heightened financing constraints and diminished innovation. This effect is particularly pronounced in central and western regions, among non-state-owned enterprises, in areas with lower environmental regulation, and for firms acquiring land through public bidding processes.

These findings carry important policy implications. First, reforming land market mechanisms: Excessive inflation in land prices exacerbates corporate carbon emissions, highlighting the urgent need for land market reforms. A shift from “policy-driven” to “market-driven” land pricing mechanisms requires the establishment of a transparent property rights system, reduced monopolistic control by local governments, and greater market participation. Unlike existing macro-level reforms, this study advocates for micro-level adjustments, such as incentivizing firms to adopt low-carbon technologies through land use zoning policies tied to environmental performance. However, market reforms should be designed with safeguards to prevent speculative activities or unintended resource misallocations. Policymakers must ensure robust oversight mechanisms to balance market efficiency with environmental objectives.

Second, mitigating financing constraints: Financing constraints, exacerbated by rising land costs, hinder firms’ ability to invest in R&D and clean technologies. Policies that expand inclusive financing, such as targeted industrial credit lines or tax incentives for green investments, can help alleviate these constraints. Compared to previous studies that focus on direct innovation subsidies, this study highlights the need for structural financial reforms that reduce the reliance of firms on high-cost external financing. Additionally, green financial instruments like sustainability-linked bonds or loans tied to firms’ carbon reduction achievements can further support the transition to low-carbon operations. Such measures, however, require careful implementation to avoid over-leveraging or inefficient allocation of financial resources.

Third, promoting corporate innovation: Technological innovation remains a cornerstone for achieving low-carbon transitions. The government should enhance R&D subsidies, develop green technology funding programs, and strengthen intellectual property protections. Moreover, policy measures must address the innovation disparities revealed by this study, particularly by providing targeted support to firms in central and western regions and in industries heavily impacted by rising land prices. Beyond financial support, governments could establish regional innovation hubs and foster public–private partnerships to accelerate technological breakthroughs and ensure more equitable access to resources.

Fourth, tailored regional environmental regulations: This study emphasizes the importance of tailoring environmental policies to regional conditions. For central and western regions, where land price impacts are

most pronounced, a mix of enhanced environmental regulation, emissions trading mechanisms, and pollution charge-rebate programs is essential. These policies must account for the unique challenges of energy-intensive industries while balancing economic growth with sustainability goals. Policymakers should also consider developing localized incentives for adopting green technologies to address the distinct economic and industrial structures in these regions.

Finally, integrating land policy with environmental goals: Unlike previous approaches that treat land policies and environmental regulations separately, this study advocates for their integration. For example, environmental zoning policies can directly link land pricing to carbon intensity targets, ensuring that land use decisions align with sustainability objectives. Dynamic land-use planning that adapts to evolving environmental priorities can also enhance the long-term coherence of these policies. However, the integration of these policies may increase administrative complexity, necessitating streamlined governance structures and inter-agency coordination.

Future research could build upon this study by addressing its limitations and exploring new dimensions. Expanding the data range to include more recent years would help capture the evolving dynamics in the land price–carbon emission relationship, particularly under contemporary policy and technological contexts. Broadening the sample to include firms from diverse industries and countries could enhance the generalizability of the findings and provide cross-country comparative insights. Incorporating additional variables, such as green finance policies, environmental taxes, or urbanization metrics, could offer a more comprehensive understanding of the factors influencing land prices and carbon emissions. Employing advanced causal inference methods, such as regression discontinuity designs (RDD) or propensity score matching (PSM), could further strengthen the identification of causal relationships. Moreover, future studies should use multiple indicators of innovation—such as R&D expenditures, product launches, or inter-firm technological collaborations—to better capture the multidimensional nature of innovation. Longitudinal studies investigating the long-term effects of sustained land price increases on corporate sustainability transitions, particularly in relation to global carbon reduction targets, would also provide valuable insights. By pursuing these avenues, future research can deepen our understanding of the interplay between land prices, innovation, and environmental outcomes.

Data availability

The datasets used and analyzed during the current study available from the corresponding author on reasonable request.

Received: 25 June 2024; Accepted: 8 January 2025

Published online: 29 January 2025

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Acknowledgements

We thank all the authors for their efforts and the Foundation's support, as well as the editors and reviewers for their dedication.

Author contributions

L.G., Z.J. and Y.L. wrote the main manuscript text. L.G. prepared figures and Z.J. prepared the tables. All authors reviewed the manuscript. Additionally, we would like to add Y.L. as co-first authors due to her significant contributions during the revision stage of our paper. Y.L. took on a central role in the revision process. Due to several original authors being unable to dedicate enough time to address the reviewer's comments, Y.L. took on the majority of the revision work, making substantial contributions, including addressing the reviewers' detailed feedback, refining the manuscript, and improving its overall quality. Her contributions went beyond simple

corrections and included significant reworking of key sections, resulting in a clearer and more robust paper. Y.L. played a central role in ensuring the paper's responses aligned with the reviewers' expectations and improved its overall academic rigor. Furthermore, they have committed to being involved in the ongoing revisions and improvements of the paper until its publication.

Funding

The research was funded by the Doctoral Research Innovation Program of Shandong Second Medical University (Grant No. 041174).

Declarations

Competing interests

The authors declare no competing interests.

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