frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 16 May 2024
DOI 10.3389/fenvs.2024.1356291

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OPEN ACCESS

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RECEIVED 15 December 2023
ACCEPTED 19 April 2024
PUBLISHED 16 May 2024

CITATION
Gao Z, Cai L and Zhang X (2024), New industrial land use policy and firms' green technology innovation in China—an empirical study based on double machine learning model.
Front. Environ. Sci. 12:1356291.
doi: 10.3389/fenvs.2024.1356291

New industrial land use policy and firms' green technology innovation in China—an empirical study based on double machine learning model

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China is facing a serious land resource mismatch problem, which will profoundly affect the acceleration of economic growth and technological innovation. Reform of the industrial land allocation system can solve the mismatch of land resources, and that also has an important impact on the promotion of economic and technological development. This paper selects the data of Chinese A-share listed companies in Shanghai and Shenzhen from 2007 to 2020 as the research sample, constructs a double machine learning model, and empirically investigates the impact of a new industrial land use policy on firms' green innovation behavior. The study shows that: (1) the new industrial land use policy significantly promotes firms' substantive and strategic green technological innovation, and the effect on substantive green technological innovation is greater than that on strategic green technological innovation. (2) The enhancement of R&D investment sustainability and the "talent pool" effect are important mechanisms through which the new industrial land use policy influences firms' substantive and strategic green technological innovation. Meanwhile, the new industrial land use policy is conducive to firms' green co-innovation. (3) There is heterogeneity in the effect of the new industrial land use policy, which can significantly promote green technological innovation of firms in the eastern region, while it does not play a significant role in the green innovation behavior of firms in the central and western regions. The above research results enrich the research in the field of industrial land and innovation, help to understand more comprehensively the mechanism of new industrial land affecting firms' green technological innovation, and provide policy insights for strengthening the application of industrial land allocation reform in firms' green innovation.

KEYWORDS

new industrial land use policy, green innovation, China, double machine learning, R&D investment sustainability, talent pool

1 Introduction

China has achieved rapid growth for more than 4 decades by relying on an abundant land supply, large labor inputs, high energy consumption, and high capital. This pattern of economic growth has been called "unsustainable growth" (Young, 2003; Wang et al., 2023a). Rough development and trade liberalization have all contributed to China's energy constraints and environmental pollution problems becoming more and more prominent, and has also caused ecological environmental protection and economic development to be on the verge of imbalance (Hao et al., 2006; Wang et al., 2023b). Firm innovation has always been an important part of national innovation development, and the importance of innovation for industrial manufacturing industries is far greater than that of other industries (Hsu et al., 2014). At the same time, green technology innovation is an inevitable choice to balance economic growth and ecological environmental protection. Compared with traditional innovation, green innovation is a new innovation model that deals with energy saving, pollution control, recycling waste, and designing green products (Tsai and Liao, 2017). Green innovation has both the economic characteristics of improving the productivity and competitiveness of firms and the social characteristics of energy saving, emission reduction and environmental protection (Wang et al., 2023c). Green technology innovation is an important force for China to get out of economic difficulties, cope with the environmental crisis, break the energy constraint and promote the construction of innovation-driven country (Wang et al., 2023d). Green technology innovation is also a key initiative for China to grasp the major opportunities of the new round of technological revolution and industrial change. According to Xinhua News Agency on 24 October 2021, the article "Opinions on Complete and Accurate Comprehensive Implementation of the New Development Concept to Do a Good Job of Carbon Peak and Carbon Neutrality" explicitly proposes to strengthen the major green and low-carbon technological research and popularization of its application, in order to support the establishment of a green, low-carbon and recycling development of the economic system. In recent years, China has accelerated the construction of innovative country and innovative cities, which has promoted the development of green technology innovation. According to data from the State Intellectual Property Office, China has been an important contributor to global green and low-carbon technological innovation. From 2016 to 2022, the global patent authorization for green and low-carbon technology inventions reached a cumulative total of 558,000 pieces. Chinese patentees were granted 178,000 pieces, accounting for 31.9% of the global share. The average annual growth rate of green patents in China reached 12.5%, significantly higher than the overall global level of 2.5%. At the same time, the problems of few high-quality patents and low utilization rate of results transformation are still prominent, and China's green technology innovation is still seriously disconnected from the actual demand (Show et al., 2018).

As a necessary input factor and spatial carrier in the production or innovation process of firms, the way land is configured and the supply strategy will inevitably have a profound impact on the production and innovation of firms. Local governments in China have taken advantage of the unique arrangement of land policy to dominate economic development. On the one hand, local governments have promoted industrialization by offering industrial land at low prices to attract investment. On the other hand, they have been able to obtain funds for building urban infrastructure and promoting urbanization by offering commercial and residential land at high prices and promoting land mortgages. The rapid structural change driven by land created China's growth miracle (Gao et al., 2021). In China's land factor market, land resource allocation is not entirely subject to market mechanisms. China's current land system gives local governments control over the allocation of land resources. As managers and suppliers of land, local governments are subject to both economic performance constraints and market regulation in land resource allocation. Local governments' land grant decisions are often accompanied by a greater degree of resource mismatch and negative externalities (Lu and Xiang, 2016; Xie et al., 2023) For example, local government officials with limited tenure tend to opt for the strategy of attracting investment through the establishment of industrial parks. So they offer as much industrial land as possible at low prices during their tenure. They are more concerned with the short-term fixed-asset investment that the project will bring than with the future growth in gross industrial output that the project will bring to the city. Intense competition for investment will prompt local governments to further reduce land prices, lower entry barriers and open their doors to industries with poor prospects and overcapacity. The entry of these "low-level" firms will crowd out scarce land resources, while creating a "crowding-out effect" on technology-intensive, capital-intensive and cleaner high-value-added industries. This model may lead to a lack of public service systems and a disconnection of supporting facilities, making cities less attractive to factors such as talent and capital. Ultimately, it leads to difficulties in building an urban innovation system to support green, high-quality local development.

Literature related to this paper can be categorized into two main groups, one of which is on the impact of the land system on economic development and other aspects. This type of literature mainly carries out research in the following four aspects. In the first aspect, the impact of local government's land transfer price strategy on government land revenue, urbanization, enterprise investment and industrial structure upgrading is studied from the perspective of government officials' incentives (Wang and Hui, 2017). The land grant price strategy is specifically manifested in the fact that local governments pursue the maximization of local finance by granting commercial and residential land at high prices. Meanwhile, they grant industrial land at low prices in order to achieve the goal of economic growth. In addition, there is a kind of bottom-line competition for the quality of attracted capital in the government's land concessions, which leads to the poor quality of the projects that are attracted. In the second aspect, the impact of industrial land resource mismatch on firm productivity is studied. For example, Li et al. (2016) found that the crude land grant, which is dominated by low land prices and agreement granting methods, impedes the improvement of resource allocation efficiency among industrial firms. In the third area, the impact of the allocation of urban construction land targets on the Chinese real estate market, the elasticity of China's housing supply, and firms' investment is investigated (Han and Lu, 2017; Shen et al., 2018; Wang et al., 2023e). For example, Han and Lu (2017) find that regions with tighter land grants have faster rising house prices, which is less favorable to firms' real investment. On the one hand, high house prices enable firms to obtain loans and increase investment by increasing the value of collateral. On the other hand, there is a "crowding-out effect" of high house prices, which discourages firms from investing. Rising house prices attract firms to hold investment property and reduce investment in fixed assets. The fourth aspect is to study the impact of land supply on environmental pollution, energy consumption and other aspects (Zheng and Shi, 2018; Li J. et al., 2023). Another category of literature is the research on the influencing factors of green technology innovation. Scholars mainly focus on the impact of governmental factors on green technology innovation, such as environmental regulation, tax policy, government subsidies and green financial policies (Jia and Ma, 2017; Miao et al., 2019; Wu and Hu, 2020; Rao et al., 2022). Some literature has begun to focus on the relationship between land markets and innovation, such as land marketization and urban innovation (Cheng et al., 2022), land resource allocation and firm innovation (Ma et al., 2022), land resource mismatch green technological innovation (Gao et al., 2021), but the above studies are relatively macroscopic, focusing mostly on the provincial and regional levels. The literature focusing on the impact of land reform on firm-level innovation is relatively scarce. At the same time, China is implementing a new industrial land use policy, but the impact of this policy on firm innovation has not been studied by scholars. This paper focuses on the new industrial land policy and examines its impact on firms' green innovation. This will complement research on land system reform and firm innovation.

Based on this, this paper takes 3,574 listed companies in China from 2007 to 2020 as the research object, and systematically examines the impact of new industrial land use policy on green technological innovation through the construction and measurement of a double machine learning model. This paper finds that the new industrial land use policy significantly promotes substantive green innovation and strategic green innovation of firms within the pilot cities, and has a greater impact on substantive green innovation than strategic green innovation. The reason is that the implementation of the new industrial land use policy improves the scale of R&D investment and the continuity of R&D investment, and then promotes firms' green technological innovation. On the other hand, the new industrial land use system exerts the effect of "talent pool", attracts high-level talents, and increases the proportion of technical talents in firms, which in turn affects firms' green technological innovation. The heterogeneity study shows that the new industrial land use policy has a significant impact on the green technology of firms in the eastern region, but not in the central and western regions of China. Compared with non-heavily polluted industries and politically connected firms, the new industrial land use policy has a stronger promotion effect on firms in heavily polluted industries and politically connected firms.

The marginal contributions of this paper may be as follows: first, using China's new industrial land use policy as an entry point, this paper empirically tests the impact of industrial land use policy on firms' substantive and strategic green innovation, enriching the current literature on land and innovation. Second, this paper uses a double machine learning method in the empirical research process. Compared with the traditional causal inference method, the double machine learning model does not require complex and strict strong assumptions. For example, when the sample data do not satisfy the balanced trend test of the double difference method, the empirical research can be carried out by the double machine learning modle, which broadens the current research method. Third, with the help of micro-level data, this paper confirms the impact of the new industrial land use policy on firms' green technological innovation and cooperation innovation, as well as its mechanism and heterogeneity. This study provides a theoretical basis for further promoting the replication and scaling up of the new industrial land use policy in China.

The remainder of the paper is organized as follows: The second section describes the evolution of China's land system and the implementation of the new industrial land use policy. The theoretical mechanism of the new industrial land use policy affecting firms' green innovation is analyzed. The third section introduces the model and data used in this paper. The fourth section reports the basic regression results of the new industrial land use policy affecting firms' green technology innovation, as well as a series of robustness tests, heterogeneity and mechanism analysis results. The fifth section further discusses the empirical findings of the article. The sixth section summarizes the full paper.

2 Policy background and theoretical mechanisms

2.1 Policy background

China's State Council promulgated the "Interim Regulations on the Granting and Transfer of State-owned Land Use Rights in Urban Areas" in 1990, which gave local governments monopoly development rights in the primary market for state-owned construction land. At the same time, the "Regulations on the Implementation of the Land Administration Law of the People's Republic of China" was introduced in 1998, which further signaled that local governments had the right to franchise and trade in land resources. In the early 21st century, motivated by the dual incentives of local fiscal revenue and regional competitive objectives, local governments in China have used industrial land concessions at low prices as a key focus for investment attraction and economic development (Chen and Kung, 2016). Since then, the competition for land attraction has been increasingly characterized by bottom-line competition, with local governments arbitrarily suppressing the real price of industrial land. This not only reduces the quality of investment attraction, but also further leads to a very serious waste of land resources and a mismatch of resource within cities. In response to the above problems, China has introduced a series of policies to curb the trend of illegal land transfers. In 2002, the former Ministry of Land and Resources promulgated the "Regulations on the Tendering, Auctioning and Listing of State-owned Land Use Rights", which for the first time stipulated that operational land, including land for commerce, tourism, entertainment and commercial residential land, had to be transferred through tendering, auctioning and listing. In 2006, the "State Council's Circular on Relevant Issues on Strengthening Land Regulation and Control" further explicitly required that industrial land must also be sold by tender, auction and listing. To a certain extent, this system avoids the inefficiency problems caused by government monopoly, improves the transparency of the decision-making process, and facilitates supervision by higher levels of government and the public. In 2007, China's former Ministry of Land and Resources promulgated the "National Minimum Pricing Standard for Industrial Land Sale", which for the first time set out clear regulations on industrial land transfer prices at the national level. This has led to land supply constraints and higher land costs in eastern China, and the large stock of inefficiently utilized industrial land prevalent in all regions has become an important constraint on high-quality economic development.

With industrial development and firm production innovation, the traditional management of industrial land has been unable to meet the innovation needs of industries. Innovation-led development objectively requires that innovation factors continue to cluster towards industrial entities. In 2006, Beijing issued the "Detailed Control Plan for Beijing Central City", taking the lead in exploring the use of industrial land for R&D. In 2015, the Ministry of Land and Resources issued the "Guidelines for Implementation of Industrial Land Use Policy". On the basis of this policy, local governments may make land use proposals to the urban and rural planning departments at the same level and to higher-level industry authorities for new industries and new business forms that are not specified in the current national standard classifications. Local governments can prioritize the supply of land for new industries and implement flexible supply of industrial land in various ways. By transforming land use to guide the development of innovative industry clusters, local economies can adapt to the new normal of economic development. Against this background, some Chinese cities have successively introduced land use policies applicable to new types of industries in accordance with the direction of regional industrial development from the perspective of land use standards, planning layout, industrial land reserves, land supply, and project construction. They explore a new industrial land management model, which mainly focuses on the policies of land spatial planning, land use control, land use planning arrangement, land supply, land utilization, and real estate registration involved in specific industries (Mi, 2022). As of December 2020, a total of 28 cities in China have implemented the reform of the new industrial land use policy, adding innovative industrial land to existing industrial land, commercial service facility land, or R&D headquarters land. The main features of new industrial land use include: first, the upper limit of plot ratio has been raised. Most cities have adjusted the plot ratio for new industrial land use to 5.0–6.0, and some cities have even abolished the upper limit. This work has led to an increase in the intensity of land development. Second, industrial supporting construction is improved. The new industrial land use policy grants a certain proportion of supporting services to the land parcel, which is not entirely industrial or commercial land. The subject of land use and development can plan supporting facilities and space according to the requirements of industrial support and development trends. This allows new industrial land projects to aggregate a variety of industrial forms. Third, land prices have become more favorable. The new industrial land use policy has set high standards for the resident firms, and only those firms that meet the standards can enjoy the preferential land use policy. For example, whether the main business of the firm belongs to the scope of policy encouragement, and whether the firm is a listed company or unicorn enterprise will all affect the admission of the firm.

2.2 Theoretical mechanisms

As one of the important factors of production indispensable to the operation and development of industrial firms, land provides the basic factors of production for the debugging of equipment and R&D innovation. It also increases the initial investment in research and development innovation of firms. China's new industrial land policy has increased the plot ratio of buildings and the development intensity of land, thereby facilitating industrial firms' access to industrial land. This provides production factors and test sites for firm production and R&D, and fulfills the function of land as a production factor. It improves the economies of scale of land and facilitates the enhancement of firms' green technology innovation capacity. On the other hand, China's local governments once used low-priced land supply as an important means of investment attraction behavior while showing obvious characteristics of bottom-line competition (Chen et al., 2018). A large number of low-end manufacturing firms with weak R&D capabilities were able to invest in industrial parks due to lower land costs. This low-priced and wide-supply industrial land strategy attracted a large number of inefficient, high-consumption, and high-pollution low-end manufacturing industries to cluster (Tang et al., 2018; Zheng and Shi, 2018). Following that, a huge scale of low-end manufacturing capacity with backward technology and low technological content has been formed on the scarce industrial land. It squeezes out investment in high-end manufacturing and emerging industries with strong innovation capacity (Zhou et al., 2021). This mismatch of land resources has driven the rapid development of high-emission and high-pollution firms, but it has also inhibited the incentives of firms to strengthen green technological innovation and greening development (Huang and Du, 2017; Luo et al., 2018; Gao et al., 2021; Du et al., 2023; Li R. et al., 2023). Meanwhile, under the new industrial land use policy, the government requires firms to have high innovation ability as well as low pollution emission. Otherwise, industrial firms will face the risk of being retired and the land they use will be taken back as inefficient industrial land. Local governments revitalize that land again. Thus, the new industrial land use policy will push firms to accelerate their green technological innovations in order to meet the appropriate standards.

Hypothesis 1 (H1). The new industrial land use policy promotes green technological innovation in firms.

New industrial land policy can promote the growth of R&D investment. As one of the long-term fixed assets of a firm, land can be used as a collateral asset for firm financing. It alleviates the agency cost, adverse selection and incomplete contract problem under information asymmetry in the debt financing process of firms (Berger et al., 2011). The traditional industrial land use policy has restrictions on the development and use of the subject of the functional limitations and sale, resulting in a contradictory situation of idle real estate resources and enterprise financing constraints. The new industrial land policy enables industrial firms to enjoy more favorable land prices. At the same time, each development zone in order to increase investment will also give relevant supporting preferential policies. So that the cost of firm land is lower, will reduce the occupation of internal funds, and enhance the internal financing ability of firms. Split sales of the new policy is also conducive to reducing the pressure on firm funds, reduce the squeeze on innovation funds. Under the new industrial land use policy, local governments have promoted the increased availability of land resources to firms by setting higher plot ratios for industrial land. Firms can more easily acquire industrial land as collateral for firms' external financing, which will substantially increase firms' credit capacity (Chaney et al., 2016; Cheng et al., 2022). In the context of China's imperfect financial market and predominantly bank credit, the increased availability of land resources will provide an important source of credit for firms' R&D innovation. Firms' innovation is highly sensitive to internal capital endowment due to the long cycle and uncertainty of R&D investment (Brown et al., 2013) Therefore, loose financial conditions will stimulate R&D activities, which is conducive to the acceleration of technological innovation and the improvement of green innovation performance (Du and Li, 2019; Du et al., 2019; Li J. et al., 2023; Wang et al., 2023f). In the meantime, firms' R&D is not only the main way for them to gain a competitive advantage, but also an important driver of the country's economic development (Slow, 1957). Once a firm's R&D activity stops or lacks continuity, that competitive advantage quickly disappears (Tavassoli and Karlsson, 2015). R&D persistence reflects a firm's long-term knowledge accumulation and technological progress in terms of R&D investment, product development or process improvement, and it is closely related to the durability of a firm's competitive advantage (Clausen et al., 2012). The continuity and stability of R&D investment is sometimes more important to firms than the scale and intensity of R&D (Schroth and Szalay, 2010). The new industrial land use policy requires a high level of innovation. Industrial firms will not be removed from new industrial land use only if they continue to invest in innovation and vigorously promote technological innovation. Therefore, under the hard constraint of "innovate or be retired", firms will continue to increase their R&D investment to promote green technological innovation.

Hypothesis 2 (H2). Promoting the increase and sustainability of R&D funding is an important channel through which new industrial land use policy can contribute to firms' green technological innovations.

New industrial land use policy can cluster human capital. The innovative requirements of the new industrial land use policy for firms have stimulated the demand for high-quality human capital. At the same time, compared with the traditional industrial land use of a single function of the relevant provisions of the new industrial land use policy to give a certain proportion of the plot of land supporting services part. For example, Shanghai stipulates that the ancillary area should not exceed 15% of the project ceiling. Shenzhen and Ningbo set a cap of 30%. The liberalization of the policy on the supporting area of industrial land will help innovative entities to create good conditions for business services and a livable external environment in the region. For example, providing a better working and living environment for high-quality green technology innovators will help attract an influx of highly skilled personnel. Wang et al. (2022) also found that higher plot ratios are conducive to labor aggregation. Human capital is an intangible resource of firms, and highly skilled personnel are also an important force in promoting green technology innovation (Kianto et al., 2017). Baumol (1996) suggests that human resource differences are an important factor contributing to differences in innovation efficiency. On the one hand, highly skilled human capital can learn and imitate advanced technologies, as well as use them to improve production processes and create new products. Non-knowledge production unrelated to R&D is particularly important for firms in developing countries, and technology imitation activities rely heavily on engineers, technicians (Rammer et al., 2009). On the other hand, highly skilled people can enhance the development, modification, and adaptation of existing knowledge, which in turn drives the creation of new technologies (Greiner et al., 2004; Arundel et al., 2007; Goedhuys et al., 2013). Overall, this learning-by-doing model facilitates incremental innovation in firms (Grimpe and Sofka, 2009). Not only do highly educated R&D personnel hired from universities and research institutions have a significant contribution to technological breakthrough innovation in firms (Herstad et al., 2015; Arvanitis et al., 2016; Sun et al., 2020), but also experienced managerial human capital and HR can organize firm resources well and thus play a positive role in firm innovation (Capozza et al., 2018). In their study, Stuart et al. (2007) found that innovators within firms play the role of "gatekeepers", which facilitates the interaction between firms' internal and external knowledge. Good business support services can also effectively enhance the work experience of highly skilled personnel, which in turn significantly improves innovation efficiency. Highly skilled personnel not only provide manpower and knowledge support for firms' green technological innovation, but also promote the research and development and diffusion of green and low-carbon technologies, which is also conducive to the iterative development of firms' green products.

Hypothesis 3 (H3). The industrial land use policy promotes green technological innovation in firms by utilizing the "talent pool" effect.

3 Data and methods

3.1 Model design

The double machine learning (DML) approach proposed by Chernozhukov (2018) relies on a classical semiparametric theoretical framework. In contrast to traditional causal inference methods, DML does not require complex and rigorous strong assumptions, allowing it to handle a wider range of data forms and model structures. More importantly, unlike traditional machine learning methods used for causal inference, DML uses Neyman orthogonalization to overcome regularization bias. Moreover, DML uses sample partitioning to correct for overfitting bias to obtain de-biased and efficient estimation. Following Chernozhukov et al. (2018), We innovatively applies the DML model to test the causal relationship between new industrial land use policies and firms' green innovation by establishing the following regression model:

$$Y_{it} = \theta_0 \text{ Event}_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it} \mid \text{Event}_{it}, X_{it}) = 0 \tag{2}$$

where i and t represent firm and year respectively. Y_{it} is the dependent variable, representing firm i in t year's green technology innovation. Event_{it} is a dummy variable for the pilot of new industrial land use policy where the firm is located. If coefficient θ_0 is significantly positive, indicating that the new industrial land use policy has a promoting effect on firms' green innovation. X_{it} is a series of multidimensional control variable. We need to use machine learning algorithms to estimate the specific form $\hat{g}(X_{it})$. U_{it} is the error term, and its conditional mean is 0. We have directly estimated Eqs 1, 2, then we obtain the coefficient estimates as follows:

$$\hat{\theta}_0 = \left(\frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1} \frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}\left(Y_{it} - \hat{g}(X_{it})\right) \tag{3}$$

where n is the sample capacity.

Based on the above estimators, the estimation bias can be further examined:

$$\sqrt{n}\left(\hat{\theta}_0 - \theta_0\right) = \left(\frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} \text{Event}_{it} U_{it} + \left(\frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} \text{Event}_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{4}$$

$$a = \left(\frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} \text{Event}_{it} U_{it} \tag{5}$$

$$b = \left(\frac{1}{n}\sum_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} \text{Event}_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{6}$$

where a obeys a normal distribution with mean 0. It should be noted that dual machine learning uses machine learning and its regularization algorithm to estimate a specific functional form $\hat{g}(X_{it})$, which inevitably introduces a "regularity bias" that prevents the estimator from having too much variance, but also makes it unbiased. This is shown by the slower convergence of $\hat{g}(X_{it})$ to $g(X_{it})$, with $n^{-\varphi_g} > n^{-1/2}$. Thus, as n and b tend to infinity, $\hat{\theta}_0$ has difficulty converging to θ_0.

To speed up convergence, the disposal coefficient estimates are made to satisfy unbiasedness with small samples. We construct the auxiliary regression as follows:

$$\text{Event}_{it} = m(X_{it}) + V_{it} \tag{7}$$

$$E(V_{it} \mid X_{it}) = 0 \tag{8}$$

where $m(X_{it})$ is the regression function of the disposition variable on the control variable, which again needs to be estimated using a machine learning algorithm in the specific form $\hat{m}(X_{it})$. V_{it} is the error term with a conditional mean of 0.

The procedure is as follows:First, a machine learning algorithm is used to estimate the auxiliary regression $\hat{m}(X_{it})$. We can get its residual. $\hat{V}_{it} = \text{Event}_{it} - \hat{m}(X_{it})$. Second, the same machine learning algorithm is used to estimate $\hat{g}(X_{it})$. We change the main regression form to $Y_{it} - \hat{g}(X_{it}) = \theta_0 \text{ Event}_{it} + U_{it}$. Finally, $\hat{V}_{it}$ is regressed as an instrumental variable for Event_{it}, and then unbiased coefficient estimates can be obtained as follows:

$$\check{\theta}_0 = \left(\frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}\text{Event}_{it}\right)^{-1} \frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}\left(Y_{it} - \hat{g}(X_{it})\right) \tag{9}$$

$$\sqrt{n}\left(\check{\theta}_0 - \theta_0\right) = \left[E\left({V_{it}}^2\right)\right]^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} V_{it}U_{it} + \left[E\left({V_{it}}^2\right)\right]^{-1} \frac{1}{\sqrt{n}} \sum_{i\in I,t\in T} \left[m(X_{it}) - \hat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{10}$$

where $\left[E\left({V_{it}}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum\limits_{i\in I,t\in T} V_{it}U_{it}$ obeying a normal distribution with mean 0. Since two machine learning estimates are used, the overall rate of convergence of $\left[E\left({V_{it}}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}\left[m(X_{it}) - \hat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right]$ depends on the rate of convergence of $\hat{m}(X_{it})$ to $m(X_{it})$ and $\hat{g}(X_{it})$ to $g(X_{it})$, i.e., $n^{-(\varphi_g+\varphi_m)}$. Compared to Eq. 4, $\sqrt{n}(\check{\theta}_0 - \theta_0)$ converges to 0 faster. Therefore, we can obtain unbiased estimates of the disposition coefficients.

3.2 Variable settings

3.2.1 Dependent variable

Green Innovation. Drawing on the methods of Gao et al. (2021), this paper measures green innovation based on green patent data. The Green List of the International Patent Classification (GLIPC), launched by the World Intellectual Property Organization (WIPO) in 2010, is an online tool for searching information on patents related to environmentally friendly technologies. The search classifies green patents into seven categories according to the United Nations Framework Convention on Climate Change (UNFCCC), including alternative energy, transportation, waste management, energy conservation, etc., and covers about 200 topics directly related to environmentally friendly technologies. In this paper, the green patent applications of A-share listed firms were obtained from China Research Data Service Platform (CNRDS) and compared with the database search of State Intellectual Property Office (SIPO) to finally form a green patent database of listed companies with high confidence. The advantages of adopting patent data are as follows. Data availability and accuracy are guaranteed. Green patents can intuitively reflect the output of firms' green technological innovation activities, which can be categorized according to different technological attributes, and can reflect the different value connotations and contributions of innovation. The above two features make it possible for patents to measure green innovation activities with different motivations. Among them, invention patents have a high-level of technology, difficulty and innovation. Utility model patents have relatively low-level of technology, difficulty and innovation. Therefore, this paper regards the number of green invention patents as substantive green innovation and the number of green utility model patents as strategic green innovation. We take these two indicators as the dependent variables of concern in this paper.

3.2.2 Independent variable

The core explanatory variable is whether the city where the firm is located implements the new industrial land use policy. The independent variable is assigned a value of one when the city where the firm is located implements the new industrial land use policy in the sample period, and 0 otherwise.

3.2.3 Control variables

In order to accurately estimate the promotion effect of the new industrial land use policy on firms' green innovation, the following control variables are selected. Firm size (Size), measured by the natural logarithm of total assets at the end of the year; gearing ratio (Lev), measured by the ratio of total liabilities at the end of the year and total assets at the end of the year; cash flow ratio (Cashflow), measured by the ratio of net cash flow generated from the operating activities of the firm to the total assets; growth rate of operating income (Growth), measured by the ratio of operating income of the firm in the current year and operating income of the previous year minus 1; number of directors (Board), measured by the number of board of directors taking the natural logarithm of the number of directors; the proportion of independent directors (Indep), expressed as a share of the number of directors who are independent directors; the age of the firm (Age), the sample year minus the year of the firm's establishment, plus one to take the natural logarithm of the year of the establishment of the firm; the proportion of management shareholding (Mshare), measured by the number of shares held by management of the firm as a percentage of the total equity share; institutional investor shareholding (INST), measured by the total number of shares held by institutional investors as a share of the outstanding share capital; and firm ownership (SOE), which takes the value of one when the firm is a state-controlled firm, and 0 otherwise.

3.3 Data sources

This paper selects the data of 3574 A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2007 to 2020 as the research sample. The data of firm characteristics and financial data come from CSMAR database. The green patent data of firms are from CNRDS. The sample data are processed as follows. We do not focus on financial firms and have excluded the financial sector sample because the format of financial firms' statements and the structure of their assets and liabilities differ significantly from those of other firms. ST and delisted companies are no longer normal listed companies, so they are not our concern. In order to weaken the influence of sample outliers, all continuous variables are shrink-tailed at the 1% and 99% quantile. The data of urban industrial land use policy in this paper comes from the official website of each city government, which is manually collected and organized by us.

4 Results

4.1 Baseline regression results

In this paper, a dual machine learning model is used to estimate the policy effect of new industrial land policy on firms' green innovation. We set the sample split ratio to 1:4, then we solved the main and auxiliary regressions for the prediction. Table 1 shows the results of the linear regression of the impact of the new industrial land use policy on firms' green technological innovation. Columns (1) and (2) of Table 1 show the results of the dual machine learning model without and with control variables respectively, and the estimated coefficients of the independent variable are both significantly positive at the 1% statistical level. This suggests that the new industrial land use policy significantly promotes firms' substantial green technological innovation. Columns (3) and (4) show the impact of new industrial land use policies on firms' strategic green technological innovations without and with control variables respectively. The estimated coefficients on the independent variables are both significantly positive at the 1% statistical level, and smaller than those in columns (1) and (2). This suggests that the new industrial land use policy can also significantly promote firms' strategic green technology innovation. This is consistent with the conclusion of hypothesis 1. However, the effect of the new industrial land use policy on firms' strategic green innovation is smaller than that on substantive green technological innovation. This may be due to the fact that new industrial land use policies in Chinese cities explicitly require firms to meet pollution emission standards and technological innovation targets. Firms will step up their green technology efforts in order to adapt to the current industrial land use requirements. Meanwhile, although strategic green technological innovation can also enable firms to achieve the goal of reducing emissions or accomplishing innovations to a certain extent, in contrast, substantive green technological innovation is the high-quality technological innovation targeted by the new industrial land use policy. Therefore, in order to maintain competitiveness, firms will pay more attention to substantive green technological innovation.

4.2 Robustness tests

4.2.1 Changing the regression model

This paper further chooses different models to analyze and test the impact of new industrial land use policies on firms' green technology innovation. First, this paper adopts the PSM method to deal with the sample self-selection problem, and takes firms' substantive green technology innovation and strategic green technology innovation as PSM treatment variables respectively. We select firm size, gearing ratio, cash flow ratio, revenue growth ratio, number of directors, proportion of independent directors, age of the firm, proportion of management ownership, proportion of institutional investor ownership, and ownership of the firm as PSM matching covariates. Propensity scoring is performed through Logit modeling. Then the nearest neighbor matching is performed in the ratio of 1:1 to find cities in the control group that have the same or similar tendency score value as the sample tendency score of the treatment group as the matching object. We end up with a new data sample. Columns (1) and (2) of Table 2 report the regression results of the dual machine learning model by the PSM method, and the estimated coefficients of the independent variables are significant at the 1% statistical level, reflecting the positive effect of the new industrial land use policy on firms' green technological innovation. Second, the double machine learning model may have setting bias. To avoid its influence on the conclusion, this paper changes the sample split ratio of the double machine learning model from the previous 1:4 to 1:9. This helps to avoid the possible

TABLE 1 Baseline regression.

	Substantive green technology innovation		Strategic green technology innovation	
	(1)	(2)	(3)	(4)
Event	4.513***	3.224***	2.546***	1.681***
	(0.47)	(0.39)	(0.28)	(0.22)
Control variables	NO	YES	NO	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31238	31238	31238	31238

Notes:*, **, and *** indicate significant at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses. The following table is the same.

TABLE 2 Changing the regression model.

	PSM-DML		Resetting Double Machine learning Models		Interactive Model	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	3.247***	1.677***	3.152***	1.657***	2.063***	1.169***
	(0.40)	(0.22)	(0.39)	(0.22)	(0.37)	(0.21)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	31064	31064	31238	31238	31076	31075

influence of the sample split ratio on the conclusion. Columns (3) and (4) of Table 2 show the regression results after changing the sample split ratio. We can see that the estimated coefficients on the independent variables remain positive. Finally, a partial linear model based on double machine learning is constructed for analysis in the benchmark regression, and there is some subjectivity in the model form setting. In this paper, double machine learning is used to construct a more general interactive model to explore the effect of model setting on the conclusions of this paper. Columns (5) and (6) show the results of the interactive model regression with significantly positive estimated coefficients on the independent variables. This again demonstrates the reliability of hypothesis one of this paper.

4.2.2 Excluding other policy effects

Another challenge to the regression results of this paper is that in verifying the policy effect of the new industrial land use policy on firms' green technology innovation, it is inevitably disturbed by other policies in the same period. In order to ensure the accuracy of the estimation of the policy effect, this paper controls for other policies in the same period. On the one hand, during the sample period of this paper, China implemented a number of low-carbon pilot cities in 2010, 2012, and 2017 respectively, and this policy has an important impact on green innovation (He et al., 2023). To control the impact of low-carbon pilot city policies, this paper sets the policy dummy variable Low_carbon.It is assigned a value of one when the city where the sample is located has implemented a low-carbon city policy in the observation period, and 0 otherwise. The Low_carbon variable is added as a control variable to the baseline model regression of this paper, and the results in columns (1) and (2) of Table 3 are obtained. It can be seen that the estimated coefficients of the independent variables are still significantly positive when controlling for the impact of the low-carbon pilot city policy. On the other hand, the "Green Credit Guidelines" issued by China in 2012 promoted the development of green credit, which can play an important role in firms' green technology innovation (Su et al., 2022). In order to control the disturbance of green credit policy, this paper sets a dummy variable Green_credits. It is assigned a value of one when the sample of heavy polluting industries suffered from green credit policy in the observation period, and 0 otherwise. Adding the Green-credits variable as a control variable to the regression model of this paper, we get the results in columns (3) and (4) of Table 3. It can be found that the new industrial land use policy can still significantly promote firms' substantive and strategic green technology innovation.

TABLE 3 Exclusion of other policy effects and using balanced panel data.

	Excluding the impact of low-carbon pilot city policies		Excluding the impact of green credit policies		Balance panel	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	3.177***	1.381***	3.221***	1.645***	6.377***	1.914***
	(0.42)	(0.22)	(0.39)	(0.22)	(1.09)	(0.42)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	31238	31238	31238	31238	9,520	9,520

4.2.3 Using balanced panel data

Because of the unbalanced panel used in the baseline regression of this paper, the entry and exit of firms may affect the assessment of the role of new industrial land use policies on green innovation. In this context, this paper further obtains the balanced panel data of 680 A-share listed companies in China between 2007 and 2020. Based on the balanced panel data, the double machine learning model regression is applied to obtain the results in columns (5) and (6) of Table 3. As shown by the estimated coefficients of the independent variables are still significantly positive at the 1% statistical level, the conclusion that the new industrial land use policy has a positive impact on firms' substantive and strategic green technological innovations remains robustly established.

4.3 Endogeneity tests

In this paper, the PSM-DML method avoids the problem of bidirectional causality and takes into account the factors affecting firms' green technology innovation as much as possible. However, the regression analysis faces the endogeneity problem due to the inevitable omitted variables. Therefore, instrumental variable method regression is used to alleviate the endogeneity problem. In this context, this paper refers to Nathan and Nancy (2014) and uses as instrumental variables the interaction term between urban terrain relief and exchange rate, and the interaction term between urban terrain relief and interest rate respectively, which satisfy the exogeneity and correlation assumptions of instrumental variables. Meanwhile, this paper builds a partial linear instrumental variable model for double machine learning based on Chernozhukov et al. (2018), and the regression results are shown in Table 4. From columns (1) and (3) of Table 4, the estimated coefficients of the independent variables are significantly positive, and the role of the new industrial land use policy on firms' substantial green technology innovation remains significant. From the results in columns (2) and (4), it can be seen that the new industrial land use policy can significantly promote firms' strategic green technological innovations, but the effect is smaller than the effect on substantive green technological innovations. Accordingly, Hypothesis one of this paper is confirmed again.

4.4 Mechanism tests

In the theoretical analysis section, we explore that the new industrial land use policy can promote firms' green technological innovations by facilitating the sustainable improvement of innovation inputs and the increase of skilled personnel. This paper further validates these two channels of action. On the one hand, this paper uses the two indicators of innovation investment intensity and innovation investment sustainability to proxy for the R&D investment channel. The amount of firms' R&D investment as a share of operating revenue is used to measure innovation investment intensity, and innovation investment sustainability is measured based on the methodology of Triguero and Córcoles (2013). Innovation investment intensity and innovation investment persistence are put into the benchmark regression model as dependent variables respectively, and the regression results are shown in columns (1) and (2) of Table 5. As can be seen from the regression results, the estimated coefficients of the independent variables are all significantly positive at the 1% statistical level, which indicates that the new industrial land use policy can significantly contribute to the innovation input intensity and innovation input continuity enhancement of firms. In firms' innovation activities, innovation input intensity and innovation input sustainability enhancement are the key for firms to actively engage in green technological innovation, which can enable firms to maintain green competitiveness (Tavassoli and Karlsson, 2015). It can be seen that the new industrial land use policy promotes green technological innovation by enhancing the intensity and sustainability of R&D investment. Thus, Hypothesis two of this paper is proved. On the other hand, this paper uses the number of R&D personnel and the share of R&D personnel as proxies for firms' skilled human capital, where the share of R&D personnel is the number of R&D personnel as a proportion of the total number

TABLE 4 Endogeneity tests.

	IV1		IV2	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	3.809***	1.973***	3.318***	1.895***
	(0.60)	(0.40)	(0.61)	(0.41)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31192	31192	31192	31192

TABLE 5 Mechanism results.

	Intensity of innovation inputs	Sustainability of innovation inputs	Number of R&D staff	Share of R&D staff	Talent investment continuity
	(1)	(2)	(3)	(4)	(5)
Event	0.643***	0.127***	0.0710***	1.847***	0.478***
	(0.09)	(0.02)	(0.01)	(0.19)	(0.09)
Control variables	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES
Observations	21480	20454	15515	15373	8,675

of employees in the firm. The number of R&D personnel and the share of R&D personnel are put into the benchmark regression model as dependent variables respectively, and the regression obtains columns (3) to (5) in Table 5. From the regression results, it can be seen that the estimated coefficients of the independent variables are all significantly positive, reflecting that the new industrial land use policy plays the effect of "talent pool", which can significantly promote the growth of firms' skilled human capital. Skilled human capital can promote the dissemination of knowledge and accelerate technological innovation, which plays a crucial role in the green technological innovation process of firms (Sun et al., 2020). Based on this, hypothesis three of this paper is confirmed. Besides, China's new industrial land use policy can facilitate the agglomeration of various types of actors and factors because of its high floor area ratio and diversified land uses. In this context of more intensive economic and innovation activities, how the new industrial land use policy affects green co-innovation needs to be investigated. In order to promote co-innovation, China has developed a series of supportive policies. This has contributed to the fact that co-innovation has become a new way for firms to carry out technological innovation activities. However, the failure rate of R&D alliances in China is still as high as 50% and the alliance partnerships are unstable (Fan et al., 2015). Against this background, this paper further investigates the role of new industrial land use policy on co-innovation of firms' green technologies. In this paper, we obtain the data of joint applications for green invention patents of A-share listed companies from CNRDS database. The number of joint applications for green invention patents of firms is used to represent green co-innovation, as well as the share of co-innovation is proxied by the proportion of joint applications for green invention patents to the total number of green invention patent applications of firms. The co-innovations of substantive and strategic green technology are put into the baseline regression model as dependent variables respectively, and the regression obtains columns (1) and (2) in Table 6. As can be seen from the results, the estimated coefficients of the independent variables are all significantly positive at the 1% statistical level, and the estimated coefficients of substantive green technology innovation are larger. This reflects that the new industrial land use policy can significantly promote the co-innovations of firms' substantive and strategic green technology. On the other hand, the share of co-innovation as the dependent variable is put into the baseline regression model, and the regression obtains columns (3) and (4). It can be seen that the estimated coefficients of the independent variables are still significantly positive, indicating that the new industrial land use policy significantly promotes the share of co-innovations in firms' green innovation in substantive and strategic green technology.

TABLE 6 The impact of new industrial land use policies on green innovation cooperation.

	Collaborative innovative		Share of collaborative innovative	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	1.406***	0.541***	0.017***	0.013***
	(0.25)	(0.08)	(0.002)	(0.001)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31238	31238	31238	31238

TABLE 7 Regional heterogeneity tests.

	Eastern region		Central region		Western region	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	2.394***	1.122***	0.359	0.924	−0.683	−0.699
	(0.39)	(0.21)	(1.04)	(0.60)	(1.03)	(0.45)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	20914	20914	5,175	5,175	4,233	4,233

4.5 Heterogeneity tests

4.5.1 Regional heterogeneity

Due to differences in resource endowments and development stages, there are regional differences in the impact of new industrial land use policies on firms' green technology innovation. In this paper, based on the distinction between east, center and west made by the National Bureau of Statistics of China, the sample is divided into east sample, center sample and west sample depending on the province where the enterprise is located. Double machine learning regression using the sub-regional samples obtained the results in Table 7. Among them, the estimated coefficients of the independent variables in columns (1) and (2) are both significantly positive at the 1% statistical level, reflecting the fact that the new industrial land use policy can significantly promote firms' substantive and strategic green technological innovation in the eastern region. From the results in columns (3) to (6), the estimated coefficients of the independent variables are all insignificant, indicating that the new industrial land use policy has no significant effect on both firms' substantive and strategic green technology innovation in the central and western regions. The possible explanations are the competition for land between high value-added and low value-added industries, which pushes up the price of industrial land in the eastern region. Industrial land resources are also relatively scarce here. While in the central and western regions, land resources and labor supply are relatively abundant. And in the process of further developing the manufacturing industry, there are more new industrial land resources in the central and western regions (Chen et al., 2018). This results in the new industrial land use pattern in the central and western regions does not occur the innovation effect.

4.5.2 Industry heterogeneity

There may be differences in the motivation for green technology innovation among firms belonging to industries with different levels of environmental threats. This paper determines the scope of heavy pollution industries according to the "Green Credit Guidelines issued" by China in 2012, and divides the full sample of this paper into heavy pollution industry samples and non-heavy pollution industry samples. On this basis, the sub-sample regression obtains the results in Table 8. The estimated coefficients of the independent variables in columns (1) and (2)

10.3389/fenvs.2024.1356291

TABLE 8 Heavily and non-heavily industry heterogeneity tests.

	Heavily polluting industries		Non-heavily polluting industries	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	6.111***	2.392***	2.069***	1.434***
	(0.99)	(0.28)	(0.39)	(0.27)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	8,841	8,841	22397	22397

are both significantly positive, indicating that the new industrial land use policy can significantly promote substantive and strategic green technology innovation of firms in heavy polluting industries. The estimated coefficients of the independent variables in columns (3) and (4) are both significantly positive at the 1% statistical level, reflecting that the new industrial land use policy also significantly promotes green technological innovations of firms in non-polluting industries. Comparing the regression results in columns (1) and (3), it can be obtained that the estimated coefficients of the independent variables are larger for the heavily polluted industries than for the non-heavily polluted industries. This reflects the fact that the green innovation effect of the new industrial land use policy is greater for heavy polluting industries than for non-heavy polluting industries. Possible explanations are as follows. According to the relevant requirements of the new industrial land use policy, heavy polluting industries face stronger constraints and their pressure to reduce emissions is greater, which also leads to the fact that firms in the heavy polluting industries are more motivated to green innovation.

4.5.3 Firm heterogeneity

Green innovation is product, technology or process innovation on an environmentally friendly basis. Its process mainly consists of three aspects: resource acquisition, resource input and resource output. In this process, the main subjects of resource acquisition and resource investment in the early stage are firms, which need to pay a lot of time, manpower, material resources and land and other resources. Political affiliation is an important factor that affects the business development of Chinese firms. For example, firms with political affiliation have more advantages in obtaining resource subsidies (Conyon et al., 2015; Li R. et al., 2023). Specifically, if a firm' executives or actual controllers serve as deputies to the National People's Congress or members of the Chinese People's Political Consultative Conference at all levels, it means that the firm is politically affiliation. Based on this, this paper distinguishes between politically affiliated samples and non-politically affiliated samples, and obtains the results in Table 9 after sub-sample regression. The estimated coefficients of the independent variables in columns (1) through (4) are all significant at the 1% statistical level for. This shows that the new industrial land use policy can not only influence the green innovation of politically affiliated firms, but also significantly promotes the innovation of non-politically affiliated firms. Meanwhile, according to the estimated coefficients of the independent variables in columns (3) and (4) are larger than those in columns (1) and (2) respectively, the green innovation effect of the new industrial land policy on non-politically affiliated firms is larger than that on politically affiliated firms. Possible reasons for these results are as follows. The new industrial land policy makes land resources more abundant, which facilitates the access of non-politically affiliated firms to land resources and helps them to carry out innovative activities. On the other hand, in the context of the high threshold of the new industrial land policy, the risk of non-politically affiliated firms being retrenched is stronger. However, politically affiliated firms have a lower risk of being retired, thanks to their links with the government. As a result, non-politically affiliated firms will take a more cautious approach to the new industrial land use policy and endeavor to carry out green technological innovations to meet the relevant requirements of the policy.

5 Discussion

This paper examines the impact of China's new industrial land use policy on firms' green technological innovation using data from China's A-share listed firms from 2007 to 2020. The article examines the role of R&D investment sustainability and the "talent pool" in the process of new industrial land use policy affecting firms' green innovation. Although this study focuses on prefecture-level cities in China, the methodology can also be used to explore the role of industrial land policy on firms' innovation in other developing countries. In addition, this study discusses the heterogeneous effects of new industrial land policy on firms' green innovation. The specific contributions of this paper are as follows.

First of all, by reviewing relevant information and literature, this paper has sorted out the evolution of China's industrial land use system. China's industrial land system has been reforming towards marketization. Due to the mismatch between the supply and demand of industrial land and the demand for industrial innovation, various regions in China are actively exploring the new industrial land system. For example, enterprises can set up R&D organizations and build human resources housing facilities on new types of industrial land. The article sorts out the timing of the implementation of new industrial land policy in various regions of

TABLE 9 Political affiliated and non-political affiliated firm heterogeneity tests.

	Political affiliation		Non-political affiliation	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	2.872***	1.606***	3.433***	1.727***
	(0.80)	(0.42)	(0.48)	(0.26)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	10112	10112	20052	20052

China. This work helps us to empirically study the impact of new industrial land policy on firms' green innovation.

Second, this paper adopts a dual machine learning approach to analyze the causal relationship between new industrial land policy and firms' green innovation. Compared with the traditional causal inference method, the dual machine learning method does not require complex strong assumptions. Therefore, the dual machine learning method has more application scenarios than the traditional causal model. Based on the regression estimation results, we find that the new industrial land policy has a significant positive impact on both substantive and strategic green innovation of firms. The estimated coefficients of their core explanatory variables are 3.224 and 1.681, respectively. This result is consistent with the findings of Xie et al. (2023) and Li R. et al. (2023). We continue with robustness tests such as resetting the dual machine learning model, using the PSM-DML model, and excluding the effects of low-carbon cities and green credit policies. We also use the instrumental variables approach to endogeneity. We find that the article's benchmark regression results still hold.

Furthermore, this paper examines the role of R&D investment sustainability and "talent pool" in the impact of new industrial land policy on firms' green innovation. We find that the implementation of new industrial land policy can significantly promote the intensity of innovation investment and its sustainability. The estimated coefficients of their core explanatory variables are 0.643 and 0.127, respectively.

This result is basically consistent with the findings of Ma et al. (2022) and Cheng et al. (2022). Meanwhile, the new industrial land policy significantly contributes to the increase in the number and share of R&D personnel. In conclusion, the implementation of the new industrial land policy helps to stimulate firms' demand for talent and enhances their human capital. The new industrial land policy allows firms to build housing for talent security, which increases the plot ratio of the land. This policy facilitates firms to attract talents. This is consistent with the findings of Wang et al. (2022). In addition, the government supports firms to utilize the new industrial land to build public science and technology R&D platforms. Therefore, the new industrial land policy would promote joint innovation among firms. This paper tests this potential mechanism and finds that the new industrial land policy significantly promotes firms' joint innovation and increases the share of jointly filed patents in their total patents.

Finally, this paper further investigates the heterogeneous effects of new industrial land policy on firms' green innovation. The findings show that the new industrial land policy has a significant impact on firms' green innovation only in the eastern region. This is because eastern China faces a serious land resource mismatch. This hinders the development of high-end industries, as well as constrains firm innovation. When firms are provided with sufficient land supply, their innovative energies are released (Gao et al., 2021). However, the policy does not have a significant impact on the green innovation of firms in central and western China. This is due to the fact that the central and western regions of China are relatively rich in available industrial land resources. In terms of industry heterogeneity, the new industrial land policy has a greater impact on heavily polluted industries than on non-heavily polluted industries. New industrial land has higher emission requirements for firms. Heavily polluting firms will be more active in green technology innovation in order to meet the environmental requirements of that land. In addition, some scholars believe that political affiliation has a negative effect on firm innovation (Chung et al., 2016), but there is also literature that suggests that political affiliation has a positive effect on firm innovation (Jiang et al., 2023). Our results suggest that the new industrial land policy has a facilitating effect on green innovation for both politically connected firms and non-politically connected firms. However, compared to politically connected firms, the new industrial land policy has a stronger role in promoting green innovation in non-politically connected firms. Non-politically connected firms have poorer access to resources. The new industrial land policy can improve the availability of land resources, which makes it easier for non-politically connected firms to obtain industrial land. Non-politically connected firms will be more motivated to develop new green technologies.

There are some limitations in this study. First, for the identification of firms affected by the new industrial land policy, this paper is based on whether the city where the firm is located has implemented the new industrial land policy. This does not directly assess the impact of a firm's ownership of emerging industrial land on its own development. Therefore, the identification strategy used in this study may need further refinement. Second, the proxy variable used for green innovation, firms' green patent data, may not fully reflect firms' green innovation behavior. For example, although a firm's patents may not fall into the category of green patents, the firm may have cited green patents in the process of inventing patents. At this point, the firm's patent may also be green. This limitation needs to be further studied to develop more comprehensive and accurate indicators of firms' green innovation.

6 Conclusion and policy implication

6.1 Conclusion

Based on the panel data of Chinese A-share listed firms, we find that the new industrial land use policy significantly promotes firms' substantive and strategic green technology innovation. And it has a greater effect on substantive green technology innovation than on strategic green technology innovation. The sustainability of R&D investment and the "talent pool" effect are important mechanisms through which the new industrial land use policy influences firms' green technological innovation. At the same time, the new industrial land use policy can promote firms' green co-innovation. In the context of China's land resource mismatch, the new industrial land use policy significantly promotes green technological innovation among firms in the eastern region, although it has no significant impact on this Green innovation behavior among firms in the central and western regions. New industrial land use policies have a stronger impact on the green innovation behavior of firms in heavily polluting industries and non-politically affiliated firms than non-polluting firms and politically affiliated firms.

6.2 Policy implications

First of all, the implementation of the new industrial land use policy should be tailored to local conditions. The new industrial land use policy can effectively promote firms' green technological innovation in order to balance economic growth and environmental protection. This policy can also alleviate the problem of land resource mismatch. Local governments in China urgently need to further clarify the allocation of new industrial land, continuously improve the new industrial land use model, and actively promote this model in eastern China. For example, they need to rationalize floor area ratios, dynamically update the thresholds for enterprises, and scientifically identify areas for new industrial land use. Eastern provinces can learn from the digital reform of new industrial land that has already been carried out in some places, and use digital technology to fully utilize the functions of new industrial land. However, in the central and western regions of China, the new industrial land use system has not significantly affected firms' green technology innovation. On the one hand, we suggest that the central and western regions raise the target requirements for indicators of energy consumption, carbon emissions and innovation in setting up the new industrial land use policy, thereby promoting green technological innovation in firms. On the other hand, the central and western regions should be wary of the abuse of the new industrial land use policy, and should focus their efforts on fully utilizing the existing industrial land.

Second, Secondly, the new industrial land use policy should be actively utilized to gather talents and alleviate financial pressure. New industrial land generally has a higher floor plot ratio, making it possible to host more fixed facilities and economic activities on the same area of land. Meanwhile, the provision of land for R&D and staff accommodation facilities is an important advantage of the new industrial land use policy. Government departments should focus on the residential living and working needs of highly skilled and high-quality talents, and strive to strengthen the accumulation of urban and industrial human capital. This requires a comprehensive assessment of land allocation imbalances within cities. There is a need to mitigate the negative impact of the imbalance between residential and industrial land use structures on the innovative participation of talent and the accumulation of industrial innovation, and to emphasize the crowding-out effect of land use mismatches on industrial innovation talent. In addition, we have responded positively to the reasonable requests of firms and vigorously promoted the new modes of flexible and divided land grants. The allocation of industrial land needs to be more scientific. The availability of land resources for firms needs to be enhanced to ensure that firms have comparable land use and mortgages.

Third, we should explore ways to amplify the promotional effect of the new industrial land use policy on green innovation and cooperation among firms. Relying on higher plot ratios and diversified land use patterns, new industrial land can cluster market and innovation players in different production segments, as well as various economic factor resources. This new agglomeration force contributes to the dissemination of knowledge and the acceleration of technological innovation. Government departments can consider actively developing and supplying supporting land for different purposes, such as land for laboratories in universities and incubators for innovation and entrepreneurship, centering on innovation cooperation among firms or innovation cooperation among industries, universities and research institutes. At the same time, government departments can also actively explore the construction of public service technology platforms, shared laboratories, or promote the sharing of key experimental instruments and equipment on new industrial land. They should actively incorporate technological innovation cooperation into the new industrial land use policy. Local governments must strengthen the positive impact of new industrial land use policies in green knowledge dissemination and technological innovation cooperation. Efforts should be made to promote the formation of closer green technology innovation platforms and networks among various subjects.

6.3 Limitations and future recommendations

Our results suggest that the implementation of new land use policy in areas with scarce industrial land resources is favorable to firms' green innovation. This study is important for a better understanding of China's development model. However, our study focuses on the impact of new land policy pilot cities on firms. We did not get data on firms' access to land for new uses. Therefore, our study still has some shortcomings. In the future, we believe that the impact of the new land policy on firms' innovative behavior can be further explored in the data on firms' access to land for new uses. The Chinese government already publishes detailed information on each land transaction in the land market. We are collecting information on these land transactions. It is possible to put together information that identifies land purchased by firms and match each piece of land to a firm. In this way, future work can utilize more detailed land information to study the impact of the land market on various decisions made by firms. It will also be possible to explore the impact of firms acquiring land on neighboring firms. Land belongs to a resource of a fixed space. Firms operate on it, which is likely to produce space effects. Therefore, identifying the spillover effect of land resources is particularly important for the role of research on land reform. In addition, the spillover impact on suppliers and customers of firms that acquire new use land is also worth being explored. At present, scholars are increasingly concerned about the mutual influence of up and downstream firms in the supply chain. Various regions in China are actively building specialised industrial chains. They have built numerous industrial clusters and want upstream and downstream firms to cluster inside the same industrial parks. This brings about a very realistic problem that firms purchasing new use land will affect the operation of upstream and downstream firms. Therefore, we suggest using more detailed data of land transactions in future studies. At the same time, future studies should consider the spillover effects of land market reforms.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

ZG: Conceptualization, Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. LC: Conceptualization, Methodology, Supervision, Writing–original draft, Writing–review and editing. XZ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was supported by the National Natural Science Foundation of China (72203121), Youth Project of Chongqing Social Science Planning Project (2022NDQN30) and Hebei Academy of Social Sciences (ZW202301).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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