

Article

Impact of Green Finance on Chinese Urban Land Green Use Efficiency: An Empirical Study Based on a Quasinatural Experiment

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Abstract: To examine the impact of green finance (GF) on urban land green use efficiency (LGUE), we treat the Green Finance Reform and Innovation Pilot Zone (GFRIPZ) policy, implemented in 2017, as quasi-natural experiment. The results from a multi-period difference-in-difference model show that GF contributes to improving urban LGUE. This conclusion is validated further by a generalized random forest model. The mechanism analysis demonstrates that GF enhances LGUE through the effects of green technological innovation, industrial upgrading, and public green behavior. The moderation analysis further reveals that artificial intelligence can amplify the positive impact of GF on LGUE. The heterogeneity results show that the positive relationship between GF and LGUE is more pronounced in midwestern cities, non-resource-based cities, and cities with a high level of financial development. Therefore, it is essential to expand the GF pilot program in a structured manner and establish a coordinated mechanism to promote LGUE improvement through GF in different regions, thereby enhancing financial service efficiency for the real economy.



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Keywords: green finance; land green use efficiency; quasinatural experiment

1. Introduction

Urban land is an important spatial carrier for the activities of urban economies, societies, politics, and cultures [1]. To promote economic growth, many countries, including China, have engaged in large-scale urban expansion in the past few decades. However, China's economic growth has been characterized by excessive investment and overpollution, which have led to the excessive consumption of land resources, a continuous increase in carbon emissions, and ecosystem degradation [2]. Land is a fundamental resource that can support economic and social development, and demand for land is high in the new industrialization process. From a long-term perspective, China's traditional high-pollution and extensive land-use model has yet to be transformed completely, and pressure on the ecological environment continues to increase, as does the prevalence of low urban LGUE [3]. Such issues can threaten the high-quality development of the economy and society. The improvement of urban LGUE can help alleviate land resource constraints and supply-demand conflicts and solve urban development problems. Therefore, improving

LGUE is an urgent issue for China's sustainable resource use and ecological civilization construction.

Achieving carbon neutrality and addressing prominent resource and environmental constraints can help China promote its green development. A 2024 Chinese government work report proposed to steadily advance carbon peaking and carbon neutrality. The steady and continuous promotion of industrial structure optimization and upgrading will require financial support under the "dual carbon" goals, and GF will play an important role in this process [4]. GF can contribute to ecological civilization construction to attain the "dual carbon" goals and function effectively as a resource allocation engine. In June 2017, China established 10 GFRIPZ cities with the main goal of guiding financial resources toward green and low-carbon industries to support high-quality economic development. The GFRIPZ policy requires the financial institutions in the pilot areas to raise the loan threshold for polluting enterprises and provide low-interest loans to green projects to encourage enterprises to use green funds to conduct clean projects to solve environmental problems. Under the guidance of the GFRIPZ policy, an increasing amount of funds are being poured into green projects, which can provide the impetus to resolve corporate pollution control issues. Therefore, the implementation of the GFRIPZ policy can effectively expand financing channels for enterprises' low-carbon transformation, reduce financing costs, and provide important support for energy structure optimization and industrial upgrading.

As China accelerates the attainment of its dual carbon goals, LGUE has become a critical research topic in academia. Researchers have found that urban LGUE is closely related to urban characteristics such as industrial structure and technological innovation [5–7]. Due to the unique economic, political, and land ownership structures of China, scholars have explored the effects of institutional factors, such as land market reforms, land finance, and environmental performance assessments, on LGUE [8–10]. Policy and institutional improvements have a limited impact on enhancing LGUE; thus, the financial market's capital flow functions should be fully leveraged. GF, as an efficient investment and financing activity committed to environmental protection, has drawn increasing attention. Studies indicate that GF can reduce carbon emissions and improve environmental quality by supporting environmental regulations [11]. GF can also directly or indirectly participate in sustainable development projects to improve energy efficiency and reduce fossil fuel consumption and, thereby, achieve green economic growth [12]. Compared with traditional financial development models, GF can meet the current demand for carbon reduction and aligns with the inherent requirements for achieving high-quality economic development. However, the literature has failed to sufficiently connect GF with LGUE. What impact does GF have on LGUE? What are the mechanisms behind the impact? Addressing these questions can help find effective implementation paths to improve urban LGUE from the perspective of GF. In addition, the GFRIPZ policy is a model for China to explore the development path of GF from bottom to top, and evaluating the implementation effect of this policy needs to be further explored. Therefore, this paper evaluates the implementation effect of the GFRIPZ policy from the perspective of urban LGUE, providing reference and value for fully leveraging the scientific and effective nature of GF policies and promoting the construction of the GFRIPZ policy.

Based on the above argument, we employ a multi-period DID model to examine the impact of GF on LGUE. Our main research framework is shown in Figure 1. Our work contributes to the literature in four key ways. First, we consider the issue of urban land green transformation from the perspective of the impact of policy in the GFRIPZ. The existing research on the GFRIPZ policy focuses on its impact on carbon emissions, green innovation, and other aspects. Therefore, this paper innovatively attempts to explore this

topic from the perspective of urban LGUE. We incorporate the GFRIPZ policy into the analysis framework of factors that can influence urban LGUE to reveal the mechanisms through which GF can affect urban LGUE and, thus, enrich the theoretical system and empirical evidence of LGUE research. Second, we explore the impact mechanisms of GF for urban LGUE from three aspects, green technological innovation (GTI), industrial upgrading (IU), and public green behavior (PGB), and examine the moderating role of artificial intelligence (AI) in the relationship between GF and LGUE to provide scientific evidence for the overall improvement of regional LGUE. We expand the research on the mechanism of promoting urban LGUE through GF and provide a theoretical basis for the application of the GFRIPZ policy to assist in the green transformation of urban land. Third, we explore the differential impact of GF on different city types based on their geographical location, financial development level, and resource endowment to offer policy insights for the differentiated development strategies of the GFRIPZ policy. Fourth, we employ the generalized random forest model to test the robustness, extend the application of machine learning methods to causal identification, and improve the robustness of the policy evaluation in this study. This study enriches the literature on the macro-level environmental effects of GF and provides valuable insights to governments seeking to improve LGUE.

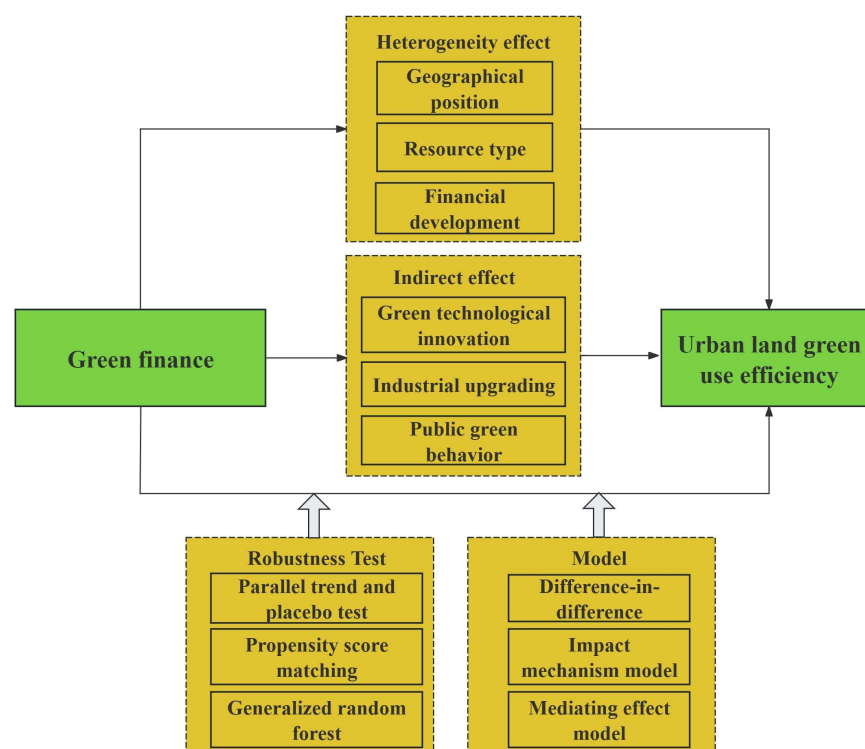


Figure 1. Research framework.

2. Literature Review

2.1. Research on LGUE

Urban LGUE reflects the overall performance of urban resource inputs and outputs. The core of urban LGUE is the maximization of economic, social, and environmental benefits by reducing land resource use and pollutant emissions. The literature on LGUE can largely be divided into two areas of discussion. The first area is urban LGUE measurement. The measurement of urban LGUE is not limited to economic outcomes but includes social and ecological indicators; thus, the DEA model has been used to analyze complex urban LGUE relationships. Although traditional DEA and SBM models have been widely

used to evaluate urban LGUE, they face challenges such as the inability to distinguish between decision-making units that are equally efficient. However, the super efficiency SBM model has addressed this issue [13,14], and scholars have employed methods such as kernel density estimation and spatial autocorrelation to reveal dynamic changes in urban LGUE [15,16].

The second area concerns factors that affect urban LGUE. Some city characteristics may affect its LGUE, such as transportation infrastructure, industrial structure, and natural endowments [17,18]. Some policy systems formed by government development concepts can also affect urban LGUE, such as land transfer mechanisms, land-based fiscal policies, and environmental regulations [19–21]. With the advent of the digital economy, scholars have examined the impact of digital economies, broadband infrastructure, and industrial automation on LGUE [22–24]. However, adequate attention has yet to be paid to the relationship between GF and urban LGUE.

2.2. Research on GF

Research on GF, as a major driving force for sustainable and green development, has become increasingly extensive. Early studies on GF focused on its definition and connotations, and the necessity and urgency of its development [25,26]. As research deepened, an increasing number of studies began to focus on the economic effects of GF. At the macro level, scholars examined the impact of GF from the perspective of regional innovation, economic development, industrial structure, and energy structure [27–30]. At the micro level, scholars evaluated the impact of GF on corporate innovation, TFP, green investment, and financing constraints [31–33].

The GFRIPZ policy, as a market-based environmental policy, can restrict heavily polluting enterprises' access to funding and, thus, guide them to increase their environmental investment for long-term development [34]. Moreover, the GFRIPZ policy can reduce environmental pollution and carbon emissions and improve corporate TFP [35,36]. The GFRIPZ policy emphasizes environmental protection and aims to provide effective financial tools and services for economic development to promote green economic growth and achieve sustainable development in both environmental and economic realms [37]. In terms of the environmental impact of the GFRIPZ policy, scholars are concerned about its impact on urban pollution emissions and air quality [38]. Furthermore, studies have found that IU, GTI, and the optimization of the energy consumption structure play an important role in promoting the GFRIPZ policy to reduce environmental pollution [39,40]. In addition, the GFRIPZ policy can work in tandem with environmental regulations to promote pollution control and, thus, substantially reduce air pollutant emissions, wastewater, and solid waste [37].

In summary, scholars have conducted extensive discussions and achieved fruitful research results in the study of GF and LGUE. Research on LGUE focuses on two aspects: measurement methods and influencing factors. The evaluation of the effectiveness of the GFRIPZ policy can be roughly divided into economic benefits, environmental benefits, and social benefits. There is currently no research on the relationship between GF and LGUE from the perspective of green finance policy. The question of whether the GFRIPZ policy can improve urban LGUE has yet to be resolved, and the mechanism between the two has remains unclear. This study provides a theoretical path and practical methods for understanding the role of GF in improving LGUE and establishes theoretical support for optimizing and improving GF policies in the future.

3. Research Hypotheses

3.1. Direct Impact of GF on Urban LGUE

In economic development, funds are typically used to expand the economic scale. Local governments typically prioritize the growth of secondary industries by attracting investment to increase the economic scale. Due to limited capital availability, local governments often rely on land development. By offering abundant and inexpensive construction land, governments can attract investment and substitute land for other production factors, which can lead to urban land-use inefficiency and exacerbate environmental and ecological issues [41]. At the same time, traditional finance can provide low-interest funds for urban economic development through monetary circulation and credit channels and lower the financing costs of land developers, which can lead to the conversion of a substantial amount of land into construction land [42]. Such conversion can not only cause environmental pollution but also exacerbate conflicts between residents and land use. However, with the introduction of the GFRIPZ policy, credit availability can restrict the capacity of heavily polluting industries to expand their scale and, thus, improve LGUE.

Specifically, GF can improve urban LGUE through several pathways. First, GF can provide financial support for green projects by reducing the associated risks through re-lending and the establishment of specialized guarantee mechanisms, thereby reducing land pollution and waste emissions during production [43]. For example, financial institutions in the Huzhou pilot zone in Zhejiang province have launched the “Green Park Loan”, which incentivizes polluting enterprises to enter the park for development through industrial agglomeration and chain-based financial services. This initiative effectively promotes land conservation and pollution prevention and control, while assisting polluting enterprises in their green transformation. Similarly, the Quzhou pilot zone in Zhejiang province targets the local metal smelting industry and introduces safety and environmental liability insurance, combining safety production with environmental pollution control to provide risk protection for green production in enterprises.

Second, GF can lower interest rates and relax loan restrictions to guide funds toward green industries, thereby reducing enterprises’ financing costs and encouraging green transformation. For example, to leverage the supportive role of GF in the development of green industries and ecological environment protection, the Lanzhou pilot zone in Gansu province has launched innovative GF products such as “photovoltaic loans” and “wind power loans” with lower interest rates and established a financial service platform to provide comprehensive financing services for green enterprises. In addition, the Hami pilot zone in Xinjiang has launched renewable energy subsidy loans to address the difficulty of financing for new energy enterprises, effectively increasing the loan scale for these enterprises. Third, GF can alleviate enterprises’ financial burden through green loans and tax incentives, thereby encouraging the production of green products. Fourth, GF can set high loan thresholds for polluting enterprises, which can increase their land-use costs and lead to the elimination of land-intensive traditional industries [44], thereby optimizing the land-use structure and enhancing LGUE. Therefore, GF can improve LGUE. On this basis, the following assumption is made:

H1. *GF can promote the improvement of urban LGUE.*

3.2. Indirect Impact of GF on Urban LGUE

3.2.1. GTI Effect

The optimal clean technology development level may not be reached through sole reliance on market mechanisms owing to failures in the research and development (R&D) market, thereby making government incentives through financial mechanisms crucial.

GF reforms and innovation pilot policies can reduce the financing costs of innovation entities involved in green technology development and, thus, lower barriers to GTI [43]. Specifically, such pilot policies can provide favorable environments for green innovation by issuing a series of incentive policies for technology R&D, transformation, and application and injecting vitality into the green innovation sector through financial support and policy guarantees. In addition, GF can provide better financing conditions for enterprises that meet environmental standards by offering low-interest loans, enabling them to easily obtain innovative capital and invest in new technology research and production optimization. This incentive mechanism helps to form a long-term technology-driven green productivity advantage and drive the improvement of the GTI level. GTI can enhance LGUE by reducing the reliance on labor and energy resources, improving the conversion rate of production factors, and minimizing resource waste and pollutant emissions during land-use activities. GTI can improve the environmental benefits of land-based production activities and, thus, substantially increase LGUE [45]. Therefore, GF can improve urban LGUE by promoting GTI in the pilot regions.

3.2.2. IU Effect

GF can guide the allocation of resources toward key industries and sectors by offering substantial credit incentives and support policies. The supported industries are typically high-tech and clean-production industries. This biased supply of financial elements can exert a “crowding-out effect” on pollution-intensive sectors and, thus, facilitate the transition of the industrial structure toward technology-intensive and low-carbon industries. Furthermore, the reduction in transaction costs and optimization of the institutional environment brought about by GF can enhance administrative efficiency, which, in turn, can accelerate IU. Government preferential support also has an investment demonstration effect, which can attract new firms in the target industries and increase competition and lead to the elimination of backward enterprises. Thus, GF can contribute to the transformation of urban industrial structures into technology-intensive and low-carbon sectors [28]. Industrial restructuring can have a significant impact on carbon reduction based on land production [46]. The transformation of traditional industries typically involves the adoption of advanced production technologies, the pushing out of highly polluting enterprises, and the efficient utilization of resources, such as capital and labor, which can reduce the reliance of production activities on land resources. Therefore, GF can enhance urban LGUE through IU.

3.2.3. PGB Effect

Public participation is a critical force for implementing green consumption practices. The GFRIFZ policy encourages public attention to be given to environmental pollution issues, which can increase environmental protection and environmental rights protection awareness. By guiding banks to issue low-carbon themed credit cards and other green innovative financial products, GFRIPZ not only promotes green consumption, but also guides and changes consumers’ payment habits, advocating the concept of green living. Some financial institutions in the pilot areas have also popularized the concept of green consumption through methods such as green point rewards and the exchange of green-themed point products, effectively enhancing customers’ enthusiasm for participating in green consumption. The improvement of public awareness of green consumption and environmental protection concepts can increase the supervision and governance of local environmental issues. The public in the pilot regions may voluntarily participate in the supervision of local companies’ emissions practices and negotiations with polluting enterprises through media exposure or government complaints to ensure the effective operation and implementation of the GFRIFZ policy. As the social awareness of environmental protection increases, the

public's enthusiasm to participate in green transportation and energy-saving activities may also increase. Consumers consciously choose efficient and environmentally friendly products, which can reduce resource consumption and environmental pollution during the consumption process [47]. Meanwhile, enterprises adjust their production methods to meet the increasing demand for green products, which can further reduce land pollution and enhance urban LGUE. Therefore, GF can improve urban LGUE by promoting PGB. On this basis, the following assumption is made:

H2. *GF can improve urban LGUE through GTI, IU, and PGB.*

3.3. Moderating Role of AI

AI can improve resource utilization and enhance environmental management, thereby providing new solutions to challenges such as dynamic environmental pollution monitoring. In the realm of finance, AI can be integrated effectively with GF [48]. First, AI can help address the information asymmetry between financial institutions and enterprises by improving data-sharing and disclosure mechanisms. Such improvements can eliminate “data silos” and provide financial institutions with the necessary data to make informed decisions about green credit allocation, thereby lowering costs associated with the identification and evaluation of green projects. Second, AI can deepen banks' understanding of the varied needs of clients, and provide the necessary computational power to innovate new GF products, thereby helping meet the diverse financing demands of companies seeking to transition to sustainable business practices. Third, AI can enhance the ability of GF to match customers' needs with GF policies in a timely and accurate manner, improving the overall quality of GF services. By enabling the precise alignment of GF products with businesses' specific needs, AI can increase the effectiveness of GF services. Lastly, AI can ensure that enterprise data remains flexible and trustworthy, facilitating real-time monitoring of fund flow and enabling early detection of potential risks, thus helping to prevent unethical practices by ensuring that only genuinely sustainable projects receive GF support.

AI can strengthen the impact of GF on LGUE improvement. By reducing information asymmetry between financial institutions and green projects, AI can help optimize GF resource allocation and enable funds to flow from high-pollution industries to low-carbon sectors [49]. In addition, AI can amplify the demand-driven effect of GF by providing green enterprises with new financing channels to facilitate their transition to highly sustainable practices. Furthermore, AI can improve the precision of matching financial products to the needs of green projects and, thus, reduce the risks associated with green innovation. Such an improvement can encourage businesses to increase their investment in green technology, which, in turn, can enhance their green manufacturing capabilities. Increased investment in technological development can further reduce resource consumption, decrease emissions at the production and consumption levels, and improve LGUE. Thus, AI can serve as a positive moderating factor that can enhance the effectiveness of GF in improving LGUE. On this basis, the following assumption is made:

H3. *AI can generate a positive moderating effect.*

4. Research Design

4.1. Model Setting

From 2017 to 2021, China has established two batches of GFRIPZ, namely, Guangzhou, Huzhou, Guiyang, and other 10 prefecture-level cities established in 2017, and Lanzhou established in the second batch in 2019. The implementation time of the pilot cities is shown in the Appendix A Table A1. We use pilot cities as the experimental group and explore the

impact of GF on LGUE through the staggered DID model. The urban-level data for analysis come from CNRDS database and CNDeepData. In this study, panel data from 2010 to 2021 is utilized, encompassing 273 prefecture-level cities.

$$LGUE_{it} = \alpha_0 + \alpha_1 GF_{it} + \alpha_2 CV_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

Here, *LGUE* denotes the LGUE of cities; *i* and *t* represent the city and year, respectively. *GF* denotes the GFRIPZ pilot policy. If city *i* is included in the GFRIPZ pilot city in year *t*, it is assigned a value of 1, otherwise, it is assigned a value of 0. Coefficient α_1 reflects the impact of GF on LGUE. μ and γ represents the fixed effect of the time and city, respectively. *CV* denotes control variables (CVs).

Inspired by Jiang (2022) [50], we construct model (2) to estimate the intermediate channels of GF on urban LGUE.

$$MED_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 CV_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

Here, *MED* represents the variables, which include GTI, IU, and PGB. The logarithm of the number of green patents is used to measure GTI. The ratio of the tertiary industry value to the secondary industry value is used to measure IU. Referring to Zhou and Qi (2024) [47], we select the logarithm of the total number of passengers carried by public buses and trams per year to measure PGB.

We examine AI's moderating effect on GF's impact on LGUE based on model (3). We add the interaction term between AI and GF to model (1).

$$LGUE_{it} = \varphi_0 + \varphi_1 GF_{it} * AI_{it} + \varphi_2 GF_{it} + \varphi_3 AI_{it} + \varphi_4 CV_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (3)$$

We measure the level of AI development by the number of AI patent applications in cities. If the coefficient of GF*AI is positive, it reflects that AI can expand the role of GF in improving urban LGUE.

4.2. Variable Definitions

LGUE: Referring to existing research [23,42], this paper uses the super efficiency SBM model to measure the LGUE. The efficiency measurement index system is shown in Table 1.

Table 1. Input–output indicators.

Type	Name	Description
Input	Land	Construction land area
	Capital	Fixed capital stock
	Labor	Urban employment
Expected output	Economic benefits	Value added of the second and third industries
	Social benefits	Average salary of urban employees
	Ecological benefits	Green coverage rate of built-up areas
Unexpected output	Pollutant emissions	Industrial wastewater discharge
		Industrial sulfur dioxide
		Industrial dust

GF: We use the GFRIPZ policy implemented in China as a proxy indicator for GF. GFRIPZ is a dummy variable obtained by multiplying the dummy variables of policy

implementation time and policy experimental group. If city i is included in the GFRIPZ pilot city in year t , it is assigned a value of 1, otherwise, it is assigned a value of 0.

CVs: Based on existing research [2,3,23], we have selected some variables that can affect LGUE as CVs, as shown in Table 2.

Table 2. Descriptive statistics.

Variable	Definition	Mean	Sd	Obs
LGUE	LGUE index based on super efficiency slack-based measure-undesirable model	1.022	0.582	3276
EC	Economic development (the logarithm of GDP per capita)	10.139	0.568	3276
OPEN	The extent of opening up (total imports and exports/GDP)	0.179	0.284	3276
PS	Population size (the logarithm of the total population)	5.862	0.711	3276
ER	Environmental regulation (the logarithm of environmental protection words' frequency in city government work reports)	−5.764	0.457	3276
RD	Technology investment level (technology expenditure/local fiscal expenditure)	0.019	0.024	3276

5. Research Results

5.1. DID Results

As shown in Table 3, the coefficients of GF are positive, indicating that GF can improve urban LGUE. Regarding research on the environmental effects of GF , existing scholars have found that GF can reduce urban pollution emissions and improve the efficiency of green development [27,30]. The research results of this study also verify the positive impact of GF on urban environmental effects. Additionally, existing research has found that environmental regulations have a certain promoting effect on the LGUE of cities [51]. We also demonstrate that GFRIPZ can improve LGUE. The reliability of the conclusions in this paper has been confirmed through comparison with the existing literature.

Table 3. The effect of GF on LGUE.

	(1) LGUE	(2) LGUE	(3) LGUE
GF	0.417 *** (0.0925)	0.434 *** (0.118)	0.368 *** (0.0883)
EC		0.127 *** (0.0227)	0.286 *** (0.0573)
$OPEN$		−0.0978 *** (0.0345)	−0.0813 (0.0823)
PS		0.0983 *** (0.0138)	0.534 *** (0.175)
ER		−0.0147 (0.0208)	−0.0249 (0.0185)
RD		1.987 *** (0.449)	4.837 *** (1.823)
City FE	N	N	Y
Year FE	N	Y	Y
R^2	0.557	0.192	0.564

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.2. Robustness Test

5.2.1. Parallel Trend Test

To ensure the effectiveness of DID estimation, we need to test whether the control group and the experimental group meet the parallel trend hypothesis. There should not be a significant difference in the trend of changes in LGUE between pilot and non-pilot cities before the implementation of GFRIPZ. Only after the implementation of GFRIPZ policy will there be changes in urban LGUE in pilot areas. The parallel trend results of GFRIPZ policy are shown in Appendix A Table A2. We can find that the regression coefficients before policy implementation (Before1, Before2, and Before3) are not significant, and the regression coefficients after the implementation of the policy (Current, After1, After2, After3, and After4) are significant. To visually demonstrate the dynamic effects of GFRIPZ on LGUE, we present the results in a graph, as shown in Figure 2, which intuitively displays the parallel trend results.

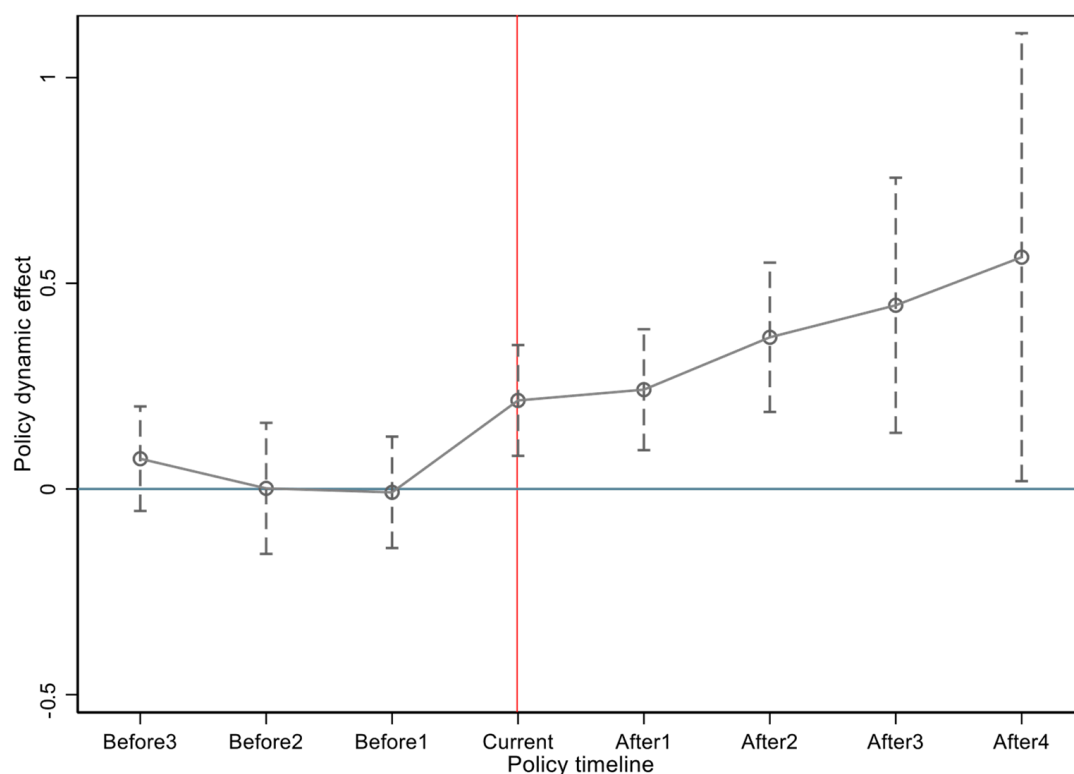


Figure 2. Parallel trend.

5.2.2. Placebo Test

Similar to the vast majority of reform policies in China, the reform targets of the GFRIPZ policy are not randomly selected. Although relevant documents suggest that the selection criteria for GFRIPZ have little correlation with urban LGUE, this non-randomness still needs to be tested to determine whether it interferes with the conclusions of this paper. To eliminate potential confounding factors, this study conducts a placebo test, repeated 500 times, based on La Ferrara et al. (2012) [52]. According to Figure 3, it can be observed that the coefficients estimated based on random samples differ from those obtained in the previous section, and the significance levels of most coefficients are greater than 0.1. This indicates that the effect of GF on LGUE is not caused by conventional random or unobservable factors.

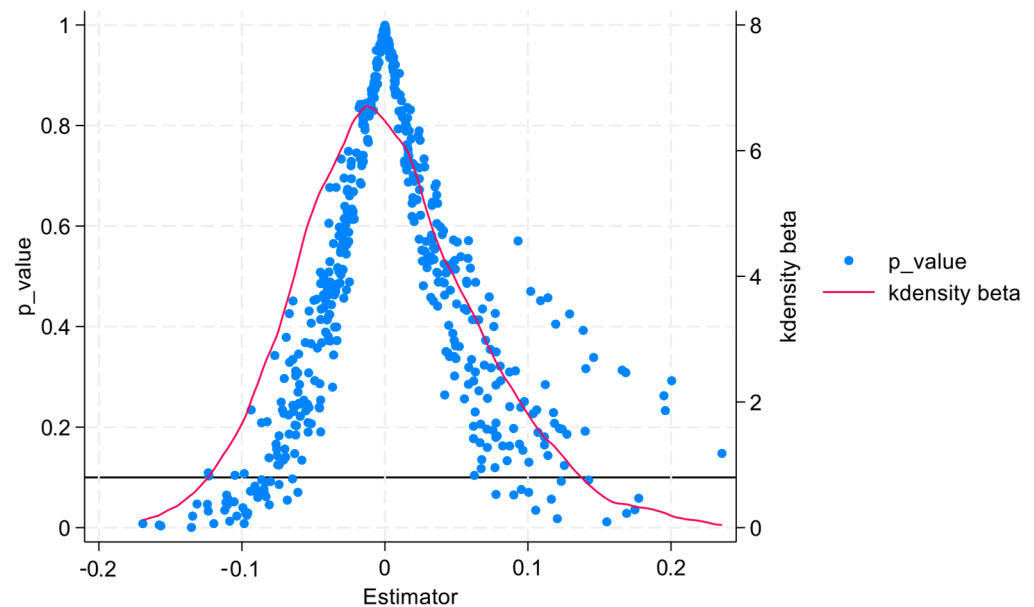


Figure 3. Placebo test.

5.2.3. Propensity Score Matching (PSM)-DID

There are significant differences between different cities. Although variables such as urban economic development level, city size, and ER are included in the benchmark regression to control for the impact of observable urban characteristics on regression accuracy, there are still unobservable and time-varying urban characteristics that can affect the accuracy of the DID model. The PSM method can effectively alleviate the influence of sample bias and irrelevant variables. The CVs selected in this paper can also, to some extent, affect the selection of pilot cities for the GFRIPZ policy. We use the CV as the matching variables for this PSM. Therefore, we choose the PSM method, using whether the sample city is a pilot city as a dummy variable, and selecting the control variables as the matching variables to construct the control group. The experimental group cities are pilot cities in the GFRIPZ, while the control group consists of cities from other regions that have successfully matched with the experimental group. The balance test results and regression results based on kernel matching and the combination of DID are shown in Appendix A Tables A3 and A4. The coefficients of *GF* are still positive, indicating that the results obtained using the PSM-DID are consistent with the benchmark results.

5.2.4. Excluding the Impact of Similar Policies

Existing research has found that some important environmental policies can affect the improvement of LGUE in Chinese cities, such as the low-carbon city policy (LCP) implemented in 2011, the carbon trading policy (CTP) implemented in 2013, and the broadband China policy (BCP) implemented in 2014, which may interfere with the results of this paper. LCP and CTP can optimize land resource allocation through market-oriented means, thereby affecting the LGUE in cities. The BCP can enhance digital technology innovation in cities and bring the Porter effect to the urban LGUE. We construct a benchmark model for the inclusion of dummy variables for the three policies based on the DID method. After excluding relevant policy interference, the estimated coefficients of *GF* in Appendix A Table A5 are still significant.

5.2.5. Other Robustness Tests

Considering that cities in the same province may have some common provincial characteristics, which can lead to serious sequence correlation problems in the residual

terms at the provincial level, we further cluster the standard errors at the provincial level. In addition, to overcome the bias of regression results caused by unobservable factors that may vary with cities and time, this paper further introduces the joint fixed effect of province–year. Columns 1 and 2 of Appendix A Table A6 show that whether adjusting for standard errors or introducing joint fixed effects, the coefficient values of GF do not change significantly compared to the baseline results. To eliminate estimation bias caused by reverse causality, this study lags all CVs by one period and includes them in the regression model (1). As shown in Column 3, the coefficient of GF is significant. In 2022, Chongqing was included in the GFRIPZ. To eliminate the possible interference caused by this event, we delete the sample of Chongqing and conduct a regression again. The result is still significant, as shown in Column 4. In 2020, the world experienced the outbreak of COVID-19, which reduced urban pollution emissions and may affect the results of this paper. We remove samples after 2019 and conduct regression again. The significance of the GF coefficient in Column 5 once again confirms the reliability of our result.

5.2.6. GRF Model Robustness Test

Athey et al. (2019) [53] proposed the GRF model, which can be applied to quantile regression, causal forests, instrumental variable models, and panel models. In this study, GRF is used to estimate the robustness of policy effects, following the methodology of Knittel and Stolper (2021) [54]. The basic steps for using GRF to estimate treatment effects are as follows: (1) A subset was randomly sampled from the full sample without replacement. (2) The subset was split into two sets: training and estimation sets. (3) A decision tree was constructed based on the training set and splitting criteria. (4) The samples were matched from the estimation set to the decision tree. Then, the treatment effects for each leaf node were estimated based on the matched samples. (5) Steps 1–4 were repeated for 2000 decision trees. (6) The average treatment effect was calculated for each individual.

The GRF model's estimation was performed using the “Causal Forests” command in the R package with default parameters. The results in Appendix A Table A7 show that as the number of decision trees increases from 500 to 2000, the average treatment effect of GF on urban LGUE remains stable at around 0.105 with no change in the standard deviation. This observation suggests that the model's precision is adequate. Although the GRF estimates are slightly lower than the DID results in Table 3, they still indicate that GF enhances urban LGUE.

5.3. Mechanism Analysis

Table 4 reports the intermediate effect test. The GF coefficients are positive, indicating that GF can improve GTI, IU, and PGB. The existing literature has found that GTI, IU, and PGB have a significant effect on enhancing LGUE. Therefore, GTI, IU, and PGB are the intermediate variables through which GF improves LGUE. Table 5 reports the regulatory effect test. The results in Table 5 show that the coefficients of $GF \times AI$ are significant, indicating that AI has a positive moderating effect. AI can play an important role in fields such as financial consulting and analysis through its powerful computing power and abundant data resources. For example, intelligent customer service understands user issues through natural language processing technology, provides accurate and personalized services, reduces labor costs, and improves service efficiency, thereby better assisting GF in improving LGUE. Therefore, AI can expand the effect of GF in improving LGUE.

Table 4. Mechanism test.

	(1) GTI	(2) IU	(3) PGB
GF	0.0623 * (0.033)	0.11 *** (0.0306)	0.366 ** (0.151)
EC	0.384 *** (0.0527)	0.414 *** (0.0454)	0.655 *** (0.159)
OPEN	0.292 *** (0.0742)	0.118 ** (0.0537)	−0.0601 (0.142)
PS	0.650 *** (0.127)	0.683 *** (0.0905)	0.573 ** (0.252)
ER	0.0428 ** (0.0172)	0.0153 (0.0119)	0.0610 ** (0.0309)
RD	2.587 *** (0.963)	2.127 ** (0.933)	−0.350 (3.413)
City FE	Y	Y	Y
Year FE	Y	Y	Y
R ²	0.96	0.877	0.354

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5. Regulatory effect of AI.

	(1) LGUE	(2) LGUE
GF*AI	0.011 * (0.00625)	0.01 * (0.0056)
AI	0.000415 (0.00203)	0.00224 (0.00234)
GF	0.535 *** (0.168)	0.486 *** (0.162)
CV	N	Y
City FE	Y	Y
Year FE	Y	Y
R ²	0.557	0.565

Note: Robust standard errors are in parentheses; * $p < 0.1$, and *** $p < 0.01$.

5.4. Heterogeneity Analysis

5.4.1. Geographical Position

From the perspective of regional differences, the samples are divided into the eastern region and the midwestern region. Heterogeneity analysis is conducted using sample regression. According to Table 6, GF has a more significant enhancement effect on LGUE in the midwestern region than in the eastern region. For the relatively lower level of economic development in the midwestern region, the demand for green financial products and services that promote green transformation is more urgent. The implementation of GFRIPZ can provide the necessary financial support and services, thereby promoting the GTI and IU of the midwestern region. Therefore, the LGUE enhancement effect in the midwestern region is more significant.

Table 6. Heterogeneity analysis.

	(1) Eastern Region LGUE	(2) Midwestern Region LGUE	(3) RB Cities LGUE	(4) Non-RB Cities LGUE	(5) High FDL LGUE	(6) Low FDL LGUE
GF	0.243 *** (0.0607)	0.599 *** (0.201)	0.298 *** (0.0993)	0.476 *** (0.114)	0.301 *** (0.103)	0.454 *** (0.134)
CV	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y

Table 6. *Cont.*

	(1) Eastern Region LGUE	(2) Midwestern Region LGUE	(3) RB Cities LGUE	(4) Non-RB Cities LGUE	(5) High FDL LGUE	(6) Low FDL LGUE
Year FE	Y	Y	Y	Y	Y	Y
R ²	0.612	0.531	0.527	0.588	0.558	0.567

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

5.4.2. Resource Type

Considering the resource endowment of cities, this paper introduces a heterogeneity analysis of resource-based (RB) cities and non-RB cities, aiming to reveal the differential responses of different RB cities to the policy effects of GF. According to Zhou and Qi (2022) [55], the sample is divided into RB cities and non-RB cities, and the sub-sample regression method is used for analysis. According to Table 6, GF can significantly promote LGUE in both RB and non-RB cities. However, from the size of the coefficient, the impact of GF on LGUE in non-RB cities is more significant than that in RB cities. The reason may be that RB cities have a relatively strong dependence on resource endowments, backward industrial structures, and difficulties in urban green transformation. Therefore, the GF has a relatively weak effect on improving urban LGUE in RB cities.

5.4.3. Financial Development Level

Due to differences in financial development levels (FDLs) among different cities, we conduct heterogeneity analysis based on FDL. We use the loan-to-deposit ratio to measure the FDL of cities and divide the sample into low FDL regions and high FDL regions based on the annual median for heterogeneity analysis. According to Table 6, GF has a more significant effect on improving LGUE in areas with a high FDL than in areas with a low FDL. This may be because in cities with a higher FDL, their financial system construction is relatively complete, and resource allocation is more effective. However, cities with lower financial efficiency have incomplete financial system construction, asymmetric information between green finance demand and supply, and relatively mismatched financial resources. Therefore, GF has a better effect on improving LGUE in cities with a higher FDL.

5.5. Discussion

Through the above analysis, we find that GF is an important factor in improving urban LGUE, with GTI, IU, and PGB being the mechanisms of action. Furthermore, the impact of GF on urban LGUE varies significantly across cities with different geographical locations, resource endowments, and levels of financial development. To further enhance urban LGUE and optimize GF policies, we propose the following policy recommendations:

Standardize relevant GF systems and implement diverse GF policies. China's GF construction lags far behind that of many developed countries in terms of the legal frameworks and policies related to GF, remaining in the early stages of development. Therefore, the Chinese government should improve its enforcement system at both the legislative and law enforcement levels, drawing on the experiences of developed countries, and construct an effective policy system that aligns with the laws of economic development. This would help continuously promote sustainable and healthy GF development.

Encourage collaboration among all entities involved in GF development. All GF entities, such as financial institutions, governments, and enterprises, should actively cooperate to improve the efficiency of financial services for the economy. Relevant government departments should fully consider the needs of financial institutions when formulating GF policies. Additionally, financial institutions and relevant enterprises should provide

timely feedback on their current market development status and needs. GF entities must work together to eliminate the adverse effects of information asymmetry, shorten the implementation time lag of GF policies, and play a key role in advancing GF to enhance urban LGUE.

GF can improve urban LGUE by adjusting the industrial structure and enhancing GTI. Therefore, under the guidance of GF policies, local governments should accelerate the updating and iteration of clean and high-tech industries. At the same time, local governments should optimize household registration policies for innovative talents, vigorously support scientific research, and enhance the GI level to leverage the environmental governance effect of GF. The synergistic development of AI and GF can have a significant impact on improving LGUE. In the era of AI, the government must help unlock the digital dividend and leverage AI's role in tracing, innovating, and regulating GF.

Local governments should formulate relevant policies that combine LGUE and GF, based on the geographical location, financial development stage, and land resource endowment of different regions. For example, the eastern region should actively encourage GTI and IU, eliminate old driving forces, prioritize new driving forces in land resource allocation, and achieve intensive, efficient, and green land utilization. Meanwhile, the midwestern region should avoid the transfer of environmental pollution while undertaking the relocation of industries from developed areas, striking a balance and achieving harmony between economic development and environmental protection.

6. Conclusions

GF, as a link between capital and environmental protection, is a crucial measure for promoting green development. The GFRIPZ is an innovative policy under China's new development pattern and serves as essential support for intensive land use and ecological civilization. This study uses the DID model to empirically analyze the effect of GF on LGUE and its underlying mechanisms. The key conclusions are as follows: (1) GF has a significant enhancement effect on urban LGUE. This conclusion holds even after applying the GRF method for robustness testing. (2) GF can improve LGUE by enhancing GTI, IU, and PGB, and AI can amplify the positive impact of GF on LGUE. (3) GF has a stronger promoting effect on LGUE in cities located in the midwestern region, non-resource-based cities, and high FDL cities. Policymakers play a crucial role in promoting urban LGUE. Policymakers can create an environment that fosters green innovation and contributes to a more sustainable future. This study has essential implications in various contexts. We offer several policy recommendations based on the findings of this study: First, policymakers should standardize relevant GF systems and implement various GF policies. Second, GF-related entities should actively cooperate to improve the efficiency of financial services for the real economy. Third, regulators need to support GTI and industrial structure upgrading and make guiding public green consumption an important focus of green finance policies. Lastly, local governments need to continuously innovate and improve green financial services based on the economic development characteristics of each region, in order to support the green transformation of urban land. This study contributes to expanding the research on the effects of the GFRIPZ strategy and provides practical insights and decision-making support for the continuous and efficient promotion of this policy and the improvement of urban LGUE. Due to the limitations of the usage method, there may be a limitation in this study, namely, the GF pilot policy is treated as a binary variable, which oversimplifies the potentially varying levels of implementation across cities. In the future, we will use the continuous DID method to further accurately evaluate the precise impact of GF on urban LGUE.

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Abbreviations

Green finance (GF); land green use efficiency (LGUE); Green Finance Reform and Innovation Pilot Zone (GFRIPZ); green technological innovation (GTI); industrial upgrading (IU); public green behavior (PGB); artificial intelligence (AI); difference-in-difference (DID); control variables (CVs); generalized random forest (GRF); propensity score matching (PSM); low-carbon city policy (LCP); carbon trading policy (CTP); Broadband China policy (BCP); resource-based (RB); financial development levels (FDLs).

Appendix A

Table A1. Policy implementation time.

Batch	Province	City
First batch (2017)	Zhejiang	Quzhou, Huzhou
	Guangdong	Guangzhou
	Guizhou	Guiyang, Anshun
	Jiangxi	Nanchang
Second batch (2019)	Xinjiang	Changji, Hami, Karamay
Third batch (2022)	Gansu	Lanzhou
	Chongqing	Chongqing

Table A2. Parallel trend test.

	(1) LGUE	(2) LGUE
Before3	0.106 (0.0761)	0.0736 (0.0772)
Before2	0.0354 (0.1000)	0.00152 (0.0969)
Before1	0.0369 (0.0866)	−0.00813 (0.0823)
Current	0.272 *** (0.0832)	0.215 *** (0.0819)
After1	0.293 *** (0.0909)	0.241 *** (0.0894)
After2	0.442 *** (0.105)	0.369 *** (0.110)
After3	0.509 *** (0.187)	0.447 ** (0.188)
After4	0.640 * (0.339)	0.564 * (0.331)
CV	N	Y
City FE	Y	Y
Year FE	Y	Y
R ²	0.558	0.565

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A3. Balance test results.

	Unmatched Matched	Mean		%Bias	%Reduct Bias	<i>t</i> -Test		V(T)/V(C)
		Treated	Control			<i>t</i>	<i>p</i> > <i>t</i>	
EC	U	10.454	10.12	62.3		3.94	0.000	0.88
	M	10.454	10.413	7.6	87.9	0.35	0.724	0.91
OPEN	U	0.16708	0.17379	−3.0		−3.16	0.000	0.25 *
	M	0.16708	0.18453	−7.9	−160.0	−0.41	0.679	0.35 *
PS	U	5.7266	5.901	−21.2		−1.65	0.1	1.77
	M	5.7266	5.8183	−9.2	47.4	−0.48	0.631	1.25
ER	U	−5.7446	−5.7733	6.1		0.42	0.675	1.25
	M	−5.7446	−5.7403	−0.9	85.0	−0.04	0.966	1.31
RD	U	0.0588	0.01918	101.4		10.50	0.000	4.26 *
	M	0.0588	0.05889	−0.2	99.8	−0.01	0.993	1.14

Note: Robust standard errors are in parentheses; * $p < 0.1$.

Table A4. The effect of GF on LGUE-based on PSM-DID.

	(1) LGUE	(3) LGUE
GF	0.416 *** (0.0924)	0.368 *** (0.0883)
EC		0.286 *** (0.0573)
OPEN		−0.0813 (0.0823)
PS		0.534 *** (0.175)
ER		−0.0249 (0.0185)
RD		4.837 *** (1.823)
City FE	Y	Y
Year FE	Y	Y
R ²	0.557	0.564

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

Table A5. Excluding the impact of similar policies.

	(1) Exclude LCP LGUE	(2) Exclude CTP LGUE	(3) Exclude BCP LGUE
GF	0.354 *** (0.0872)	0.368 *** (0.0884)	0.366 *** (0.0884)
EC	0.266 *** (0.0600)	0.284 *** (0.0631)	0.287 *** (0.0572)
OPEN	−0.0696 (0.0841)	−0.0815 (0.0823)	−0.0820 (0.0823)
PS	0.452 *** (0.168)	0.532 *** (0.175)	0.544 *** (0.178)
ER	−0.0244 (0.0185)	−0.0248 (0.0185)	−0.0245 (0.0185)
RD	4.487 ** (1.760)	4.829 *** (1.819)	4.699 *** (1.790)
City FE	Y	Y	Y
Year FE	Y	Y	Y
R ²	0.566	0.564	0.564

Note: Robust standard errors are in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

Table A6. Other robustness tests.

	(1) LGUE	(2) LGUE	(3) LGUE	(4) LGUE	(5) LGUE
GF	0.487 * (0.275)	0.487 *** (0.115)	0.369 *** (0.0884)	0.365 *** (0.0883)	0.286 *** (0.0693)
EC	0.347 * (0.180)	0.347 *** (0.0953)	0.301 *** (0.0633)	0.289 *** (0.0574)	0.324 *** (0.0550)

Table A6. Cont.

	(1) LGUE	(2) LGUE	(3) LGUE	(4) LGUE	(5) LGUE
OPEN	0.0213 (0.127)	0.0213 (0.0804)	−0.0780 (0.0922)	−0.0798 (0.0825)	−0.143 * (0.0775)
PS	0.858 ** (0.315)	0.858 *** (0.173)	0.418 ** (0.189)	0.537 *** (0.175)	0.318 * (0.175)
ER	−0.0287 * (0.0165)	−0.0287 (0.0185)	−0.0420 ** (0.0201)	−0.0242 (0.0186)	−0.0141 (0.0188)
RD	7.950 * (3.931)	7.950 *** (2.058)	4.301 * (2.315)	4.941 *** (1.824)	2.898 (2.275)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
R ²	0.641	0.641	0.591	0.565	0.543

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A7. GRF results.

	(1) LGUE	(2) LGUE	(3) LGUE	(4) LGUE
GF	0.104 *** (0.031)	0.105 *** (0.029)	0.105 *** (0.028)	0.105 *** (0.027)
Tree Num	500	1000	1500	2000
Model	Causal Forest	Causal Forest	Causal Forest	Causal Forest

Note: Robust standard errors are in parentheses; *** $p < 0.01$.

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