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How does the Chinese land restriction policy influence green total factor productivity?

Evidence from the Chinese cities

Ping HUA^a, Shenyang XU^{b,c}, Miao LIU^c, Yibo CHEN^c

^a *University Paris Nanterre, CNRS EconomiX, France. Email: ping.hua@cnrs.fr*

^b *School of Economics and Finance, Hohai University, Changzhou, Jiangsu 213200*

Business school, Hohai University, Nanjing, Jiangsu 211100, China

Abstract: The ample and inexpensive land supply since 1986 has contributed to the strong development of high-energy-consuming and high-polluting industries in China, becoming the world's biggest CO₂ emitter. To reorient this urban polluting industrialization towards a sustainable development, China decided in 2014 to restrict the land supply to new industrial construction in the city centers of more than 5 million populations, limiting thus the new industrial firms from setting up there. Is this restriction good for harmonizing environment and long-term sustainable development? The theoretical arguments suggest several channels through which the land restriction policy influences green total factor productivity (GTFP). They are verified by a difference-in-differences (DID) method using panel data over the 1999-2017 period for 14 cities affected by the policy as the experimental group and the remaining cities including all prefecture-level ones as the control group. The obtained results show that the land restriction policy has improved the urban GTFP via 1) improving allocation efficiency of land transfer 2) increasing land price and transforming industrial structure in favor of tertiary industry, which exert themselves positive impacts on GTFP, and 3) decreasing newly built enterprises, investment, patents for inventions, or technological innovation, which influence themselves negatively GTFP. They show moreover that the effects of the land policy are heterogeneous and stronger in eastern cities, municipalities directly under the Central Government and resource-based cities. Consequently, a selective land policy in favor of green industry is thus necessary to avoid the risk of urban deindustrialization and to promote the sustainable industrial development of the urban economy in the process of low-carbon transition.

Keywords: Land restriction policy; Green total factor productivity; Sustainable development; China

JEL classification : Q24 Q28 Q55 Q56 O13 P28 R52

1. Introduction

China's rapid industrialization has benefited from unique land system arrangements and reforms (Liu, 2017). The Land Management Law initiated in 1986 made local governments the monopolists of the primary land market (Han & Kung, 2015). By selling land, local governments have obtained huge revenues for urbanization. This "seek development through land" mode in China has resulted in an overexpansion of urban industrial construction which caused serious environmental problems (Liu & Ling, 2020). The supply of cheap land in China's cities has provided space for a large number of high-energy-consuming and highly polluting industries, which have been the main source of China's environmental pollution (Zhou et al., 2020). The quick industrialization in China is accompanied by the massive use of land resources, and the environmental pollution caused by improper land use has become increasingly serious (Geng et al., 2021). In 2007, China's carbon emissions surpassed those of the United-States, becoming the world's largest CO₂ emitter. The excessive expansion of urban construction land and its unreasonable structure are not conducive to the sustainable development of the Chinese economy and environment.

It is thus urgent to reform the land use system and optimize the allocation of land resources in favor of environment. On 13 February 2014, the Ministry of Land and Resources issued the Notice on Strengthening Controls and Implementing the Strictest Arable Land Protection System (hereinafter referred to as the land restriction policy), which emphasized that "urban construction land is strictly reviewed and in principle no more new construction land will be arranged for the central urban area of megacities with the population of more than 5 million people, except residential land and public infrastructure land".

Does this land restriction policy play a role of environmental regulation policy to reorient polluting industrialization to green one in favor of a long-term sustainable development? The recent literature suggests to incorporate energy and environmental factors to calculate green total factor productivity (GTFP). The last one is main driving force to transform towards the mode of economic development under the constraint of energy conservation and CO₂ emission reduction (Wang & Liu, 2015). Therefore, it is theoretically important to study the effects of the land restriction policy on GTFP.

The factors that could affect GTFP are numerous in an economy in transition towards sustainable development such as China, where economic policies and productive structures have changed dramatically. All these factors are potentially affected by the land restriction policy. In fact, the land restriction policy may increase land price and production cost, obligate industrial firms, in particular the polluting ones, to move outside the cities, while may decrease the opportunities for new industrial firms to invest in technological innovation and in green industry. Thus, land price and industrial structural transformation and upgrading, newly built enterprises, external investment, patents for inventions and technological innovation are potential transmission channels through which the land restriction policy exerts its impacts on GTFP, named here "indirect effects." Moreover, it is likely that the land restriction policy decided by the central government modify the behavior of local governments under the increasing pression of environmental constraints in their management and allocation of land transfer. This impact on efficiency of management and land reallocation is called "direct effects". Consequently, we argue in this study that the land restriction policy may influence GTFP either via its direct impacts on allocation efficiency of land transfer, or via its indirect effects on intermediary variables which in

return influence themselves GTFP. We then propose a theoretical model of urban GTFP to identify potential multiple impacts of the land restriction policy.

Empirically, we firstly measure urban GTFP basing Cobb-Douglas production function under environmental constraints using panel data over the period from 1999 to 2017 for 14 megacities and other prefecture-level cities. We then propose models to identify the channels through which the policy influences GTFP. We finally use the differences-in-differences (DID) method to estimate the models. The obtained results show that the land restriction policy has increased urban GTFP by ①improving the allocation efficiency of land transfer; ②rising land price and promoting industrial structural transformation in favor of less polluting tertiary industry, which influence themselves positively GTFP; ③reducing newly built enterprises, investment, invent or technological innovation, which exert themselves negatively GTFP. It seems that the land restriction policy did not promote industrial firms, leading a risk of urban deindustrialization. It seems moreover that environment was not a constraint for newly built enterprises, investment, patents for inventions and technological innovation. Consequently, a selective land policy incites the setting up of green industry, green investment, green patents and green technological innovation in cities is necessary to reorient polluting industrialization towards a green urban one and to promote the sustainable industrial development of the urban economy.

The issue of the impacts of the land restriction policy on the green total factors productivity is an important one at this time where the Chinese government is under strong pressure from the international community to decrease CO₂ emissions. Even that many studies have made on GTFP measurement and on the impacts of land resource use and environmental regulation on green development, no studies, to our knowledge, have analyzed the impacts of the land restriction policy on GTFP. This paper contributes the literature by completing the gap.

The rest of the paper is organized as following. The second section presents literature review. The third section proposes models in which research hypotheses are tested. The fourth section presents empirical results. The five section presents robustness tests. The economic and political implications are given in the conclusion.

2. Literature review

This section briefly reviews the literature on measuring GTFP green development, the impact of land resource use on green development and the impact of environmental regulation on GTFP.

2.1 GTFP measurement

TFP is traditionally recognized as a key factor in explaining long-term economic development (Letta & Tol, 2019). It is measured using capital, labor inputs, together with total output (Chen et al., 2008; Coelli & Rao, 2005; Nishimizu & Page, 1982; Pan & Ying, 2012; Wu, 2000; Yang, 2015; Yuan et al., 2015). Resource conservation and emission reduction are however two major connotations of sustainability and green development. Ignoring environmental costs and energy inputs (Feng et al., 2018; Walker et al., 2020), the models of economic development quality are over validated (Cheng et al., 2023), which biases the relevant analyses (Chen & Golley, 2014).

To remedy the shortcomings of traditional TFP, many scholars have incorporated energy and environmental costs to calculate GTFP (Sueyoshi et al., 2017; Zhou et al., 2008; Emrouznejad & Yang, 2018; Song et al., 2012; Cheng et al., 2023). The last one

is a pertinent indicator to analyze green development and sustainable economic growth (Feng et al., 2018; Lin & Chen, 2018; Liu et al., 2020, 2022; Wang & Lee, 2022). It has been measured ranging from the domestic industrial sector to various countries around the world (Chung et al., 1997; Kumar, 2006). The determinants of GTFP changes in individual countries have also been explored (Mahlberg et al., 2011). GTFP has also been studied by many Chinese scholars. The main focus was to measure GTFP on a sectoral (Chen & Golley, 2014; Li & Lin, 2015; Li & An, 2012; Tian & Lin, 2017; Xue & Li, 2011; W. Yang et al., 2017; Z. Yang et al., 2017), regional (Kuang & Peng, 2012; Li & Lin, 2016; Wang & Feng, 2015), and national levels (Zhang et al., 2011), as well as to explore the factors influencing GTFP (Li & An, 2012; Xue & Li, 2011). Furthermore, Xia and Xu (2020) used GTFP to study the quality of China's economic development, and found that there is a significant difference between TFP and GTFP because TFP ignores environmental costs. Kuang and Peng (2012) pointed out that GTFP can capture productivity losses caused by environmental issues and provincial differences in resource utilization compared to traditional TFP. GTFP is a dynamic strategy to increase productivity while maintaining environmental performance (Li & Lin, 2017). Usually, influencing factors of GTFP are green innovation (Du & Li, 2019; Luo et al., 2022; Wang et al., 2021; Wu et al., 2022), economic structure (Wu et al., 2020; Yuan et al., 2020), and economic size (Gao et al., 2021).

The previous studies measured GTFP mainly use DEA or extended DEA models that introduce non-expected outputs. The obtained results of these methods are strictly affected by the setting of the correlation function, which may bias the results. The OECD recommends the use of the Solow residual method to account for TFP based on the production function. Therefore, this paper adds the environmental factors such as land, energy factors and the special input factor of CO₂ shadow price into the traditional production function to measure the GTFP for China's cities.

2.2 Impact of land resource use on green development

Land resources are key elements of economic activities, providing the material and spatial basis for human survival and development (Cao et al., 2022; Song et al., 2020). However, rapid population growth and industrialization in the 20th century led to an increase in land development and use, and a decrease in the availability of land resources (Yang et al., 2023). The sustainable development of land resources is now facing increasing human pressures and the negative impacts of climate change (Bai et al., 2021). The multiple challenges are associated with increased land degradation, reduced biodiversity, and increased greenhouse gas (GHG) emissions. For example, some scholars have found that inappropriate land use can lead to increased GHG emissions and PM_{2.5} concentrations (Paustian et al., 2016; Su et al., 2022; Xu et al., 2022). To mitigate these negative externalities arising from land resource development, governments have attempted to regulate land resources through administrative means (Posner, 1969). For example, appropriate land use policies and ecological restoration programs can help reduce greenhouse gas emissions (Feng et al., 2013). Structural changes in land resources can reflect land use and provide a scientific basis for government land management policies (Jing et al., 2021). Therefore, the green development strategy of the Chinese government encourages the wise use of land resources to achieve the goal of sustainable development, with special emphasis on harmonizing economic growth and environmental protection (Jin et al., 2019). Some scholars have also focused on ways to mitigate environmental pollution caused by inappropriate land use (Du et al., 2023). Recent studies have shown that improving the efficiency of land resource use can significantly reduce air pollution (Ji et al., 2021; Li

et al., 2021), and new land use patterns can reduce airborne CO₂ levels (van Marle et al., 2022).

In summary, the irrational use of land resources can hurt the environment and the economy. Therefore, the formulation of policies for sustainable development requires a discussion of the impact of land policies on economic and environmental sustainability. In the field of sustainable development, GTFP is a hot issue discussed in the literature. However, there are few studies on the impact of land restriction policy, and we have not seen any literature on the impact of land restriction policy on GTFP. To complete this gap, this study takes the land restriction policy in Chinese cities as a “quasi-natural experiment” and explores the impact of land restriction policy on urban GTFP.

2.3 Impact of environmental regulation on GTFP

There is a debate on the impact of environmental regulation on TFP (GTFP) in the literature. Firstly, it is argued that well-designed environmental regulations can induce firms to innovate and bring about significant “innovation compensation” effects, increasing total factor productivity calls the “Porter hypothesis” (Guo & Zhang, 2015; Yang et al., 2012; Zhang et al., 2011). The second group of arguments supports the “compliance cost hypothesis”. It is argued that environmental regulation imposes additional environmental governance costs on firms. The negative effects of the costs of following environmental regulation policies outweigh the positive effects of incentivizing innovation. This can crowd out investment in production and has a negative effect (Hancevic, 2016; Lanoie et al., 2011; Xu & Qi, 2017). A third group of views suggests that there is uncertainty about the role of environmental regulation in influencing GTFP. They found that there are temporal and spatial differences in the impact of heterogeneous environmental regulatory policies on GTFP. Except for temporal and spatial uncertainty, the costs and effects of environmental regulation will vary by type of regulation (Cai & Zhou, 2017; Han & Hu, 2015; Lanoie et al., 2011; Li & Wu, 2017).

In conclusion, the impact of environmental regulation on TFP is theoretically uncertain, dependent which hypothesis (“Porter hypothesis” or “compliance cost hypothesis”) is higher. An empirical investigation is thus necessary to estimate it. Therefore, this paper discusses the impact of land restriction policies on GTFP in Chinese cities and analyses the impact mechanisms, intending to provide some policy insights for promoting sustainable urban economic development in the process of low-carbon transition.

3. DID models: research hypotheses to be tested

The objective of the land restriction policy is to mitigate environmental pollution caused by inappropriate land use, in particular the quick polluting industrialization, to harmonize economic growth and environmental protection and to achieve the goal of sustainable development (Jin et al., 2019; Du et al., 2023). The land restriction policy could affect GTFP via optimizing the allocation of land resources and improving its use efficiency, significantly reducing air pollution (Ji et al., 2021; Li et al., 2021), and via new land use patterns and price influencing thus industrial structure, reducing thus airborne CO₂ levels (van Marle et al., 2022). In this section, we present research hypotheses, and from which are drawn models. We proceed in forth steps. We firstly check the effectiveness of the impact of the land restriction policy on land transfer; then argue the impacts of the land restriction policy on GTFP, identify intermediary variables

which are influenced by the land restriction policy, and to estimate the direct, indirect and total effects of the Policy on GTFP.

3.1 Impact of the land restriction policy on land transfer

To explore whether the land restriction policy effectively reduces the area of land supply, a DID model is proposed as follows:

$$Land_{i,t}^c = \alpha_1 + \beta_1 Policy_{i,t} + \lambda_1 X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

where $Land_{i,t}^c$ represents the land grant of city i in year t , including the total land transfer area and the total land transfer area added. The key explanatory variable is $Policy_{i,t}$. Its coefficient β_1 captures the impact of the land restriction policy on urban land transfer and tests the policy effect of the land restriction policy. $X_{i,t}$ is a set of control variables affecting land transfer in city i in year t . η_i are city-fixed effects, and μ_t are year-fixed effects, and $\varepsilon_{i,t}$ is a random perturbation term.

3.2 Impacts of the land restriction policy on GTFP

The literature proposes three hypotheses concerning the impacts of environmental regulations on green productivity. Firstly, environmental regulations may increase the costs of firms by imposing new constraints on firms' production decisions, causing management, production, and marketing to become more difficult and TFP to fall (Christainsen & Haveman, 1981). Secondly, appropriate environmental regulation may however stimulate firms to engage in technological innovation and promote TFP through the "innovation compensation effect" and the "learning effect" which is known as the "Porter hypothesis" (Ambec et al., 2013; Li & Chen, 2013; Wang et al., 2008). Finally, environmental regulations are only a potential factor to increase TFP, and it does not directly indicate that environmental regulation increases or decreases TFP. From the above literature, we can see that there is no consensus on the impact of environmental regulation on TFP.

The land restriction policy is an environmental regulation policy of the State to reduce the over-exploitation of land, to optimize the urban land use structure, and to promote the sustainable development of China's economy, which could have impacts on the GTFP. It could reduce land supply and optimize the allocation of land resources. It could give the limited land in priority to emerging high-productivity, or technological advanced enterprises and gradually phase out some high-pollution and high-energy-consuming backward enterprises through the rise of land price. Based on this, this paper puts forward the following hypothesis:

H1: Land restriction policy could influence urban GTFP.

To test the hypothesis, the following equation is proposed:

$$GTFP_{i,t} = a_0 + a_1 Policy_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

where $GTFP_{i,t}$ represents the GTFP of city i in year t . $Policy_{i,t}$ represents the land restriction policy. The coefficient a_1 captures the impact of land restriction policy on the urban GTFP. To avoid the possible bias by the absence of control variables, the last ones are added into equation (2):

$$GTFP_{i,t} = b_0 + b_1 Policy_{i,t} + b_2 X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

$X_{i,t}$ is a set of control variables affecting the GTFP of city i in year t , including real GDP per capita, road area per capita, population, capital stock, number of labor, land area, energy consumption, human capital, fiscal deficit, and FDI etc. Thus, the coefficient b_1 captures the effects of land restriction policy which does not pass-through control variables.

Finally, we add land transfer into equation (3) such as:

$$GTFP_{i,t} = c_0 + c_1 Policy_{i,t} + c_2 X_{it} + c_3 land_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (4)$$

Thus, the coefficient c_1 captures the effects of land restriction policy which do not pass-through control variables and land transfer. A significant coefficient c_1 means there are intermediary variables which are influenced by Policy may influence GTFP.

3.3 The land restriction policy, intermediary variables and GTFP

Three potential intermediary variables are identified. They are influenced by the policy, exert impact on GTFP.

3.3.1 The land restriction policy, land prices, and GTFP

Price mechanism is a link and role of mutual constraints between price changes and changes in supply and demand in the process of market competition. The price mechanism is the most sensitive and effective regulating mechanism in the market mechanism, and price changes have a very important impact on the entire socio-economic activities. The flow of resources under the guidance of the price mechanism is regarded as the most reasonable resource allocation mechanism, which is called the “invisible hand” by Adam Smith. Transaction cost theory suggests that markets and firms are two alternative ways of resource allocation. The former driving factor flows through the price mechanism, and the latter allocating resources through internal authority relationships (Yuan et al., 2021). The implementation of land restriction policy will reduce the total supply of land, and according to the theorem of supply and demand, the price of land will surely rise. Environmental regulations can internalize the external costs of pollution. This prompting firms to redesign their production methods to reduce pollution emissions, change production growth rates, and increase the costs of new investments (Xiao & Ji, 2013). Through the resource allocation effect of “the highest bidder wins” in the market, high-efficiency firms can be screened out. When firms are willing and able to buy land at a higher price, they tend to be high-quality firms. These high-quality enterprises expand their production after acquiring land, with higher production efficiency and better technological research and development capabilities. Therefore, the land restriction policy raises the price of land, which can increase GTFP by optimizing the allocation of resources. Based on this, this paper proposes the following hypothesis:

H2: The land restriction policy will increase urban GTFP through the price mechanism.

$$GTFP_{i,t} = d_0 + d_1 Policy_{i,t} + d_2 X_{it} + d_3 Price_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (5)$$

The coefficient d_3 is expected to be positive.

3.3.2 The land restriction policy, change of industrial structure, and GTFP

The land restriction policy could modify industrial structure in favor of less polluting industry, and thus promote GTFP growth. At the micro level, it could reduce the supply of land for polluting enterprises, could force them to actively change their production methods, to adjust their production structure and to increase green production. At the macro level, the land restriction policy could eliminate polluting enterprises in favor of green ones. Industrial structure change has the role of “resource converter” and “pollutant control body” (Yu, 2017), which largely determines the direction of economic development and the quality of environmental protection, and thus becomes an important way to enhance GTFP (Yuan & Xie, 2015). This is because the upgrading of industrial structure is often accompanied by the gradual replacement of traditional industries by low-pollution, low-energy-consumption, and high-value-added emerging industries. This not only improves production factor efficiency, but also reduces the intensity of energy consumption, thus positively affecting GTFP (Liu

et al., 2018). From the general law of green development in major economies around the world, the upgrading of industrial structure is often accompanied by the continuous release of the “industrial structure dividend”. The continuous replacement of old industries by new industries leads to the gradual emergence of clean and efficient industries. This leads to the continuous optimization of resource allocation and the continuous improvement of production efficiency in the whole society, and thereby effectively supports the enhancement of GTFP (Liu & Ling, 2020). Based on this, this paper puts forward the following hypotheses:

H3: The land restriction policy will enhance the urban GTFP by promoting industrial structure change in favor of tertiary industry. This hypothesis can be tested by adding variable *Industry* into equation (3) as following:

$$GTFP_{i,t} = e_0 + e_1Policy_{i,t} + e_2X_{it} + e_3Industry_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (6)$$

Where *Industry*_{it} represents industrial structure in favor of tertiary industry.

3.3.3 The land restriction policy, technological upgrading and innovation and GTFP

The impact of technological innovation on GTFP is uncertain. The “environmental paradox” suggests that technological upgrading and innovation-oriented entirely to economic growth may ignore the negative impacts of technological innovation on resources and the environment, thus negatively affecting the improvement of GTFP (Wang, 2017). The Chinese enterprises have benefited from the low cost of environmental constraints after the reform and opening up in 1979 by ignoring environmental factors in their production for long times. This led that technological innovation and environmental pollution going in the same direction. Moreover, the “appropriateness theory” and the “productivity paradox” suggest that unsuitable technological innovations are difficult to match the development stage and factor endowment structure of an economy, which will weaken the intrinsic motivation of technological innovation, and thus is not conducive to GTFP (Kong et al., 2015; Lin & Zhang, 2006).

However, environmentally friendly technological innovation could improve resource allocation efficiency, effectively reduce energy consumption per unit of output, thereby increasing GTFP in the long term (Liu et al., 2016; Wang et al., 2020).

Enterprise technological innovation requires a large amount of financial support to respect strict environmental protection system and emission reduction constraints on enterprises. However, the land restriction policy leads to an increase in urban land prices, reducing the number of new enterprises and weakening external investment. This will inhibit enterprise technological innovation and is not conducive to the enhancement of GTFP. Based on this, this paper proposes the following hypothesis:

H4: The land restriction policy could influence urban GTFP via its effects on newly built firms, investment and patents which in turn impact firms’ technological innovation. This hypothesis can be tested as following:

$$GTFP_{i,t} = f_0 + f_1Policy_{i,t} + f_2X_{it} + f_3Firms_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (7)$$

$$GTFP_{i,t} = g_0 + g_1Policy_{i,t} + g_2X_{it} + g_3Investment_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (8)$$

$$GTFP_{i,t} = h_0 + h_1Policy_{i,t} + h_2X_{it} + h_3Patent_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (9)$$

$$GTFP_{i,t} = j_0 + j_1Policy_{i,t} + j_2X_{it} + j_3IRIEC_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (10)$$

Where *IRIEC*_{it} is a composite index of *Firms*_{it}, *Investment*_{it} and *Patent*_{it}. The coefficients of *f*₃, *g*₃, *h*₃ and *j*₃ are expected to be positive if newly built firms, investment patent, or technological innovation take environmental constraints into account; negative if not.

3.4 Direct, indirect and total impacts of the land restriction policy on urban GTFP

3.4.1 Estimating the direct impacts of the land restriction policy on urban GTFP

To estimate the direct impacts of the land restriction policy, we estimate a GTFP function including Policy, control variables and intermediary variables. As all the control and intermediary variables are added into the equation, the coefficients of Policy measures only the effects that cannot capture by the control and intermediary variables and notably the direct effects on management and reallocation efficiency of land transfer. Technological innovation is represented either by firm, investments and patent, or by their composite index, named IRIEC.

$$GTFP_{i,t} = l_0 + l_1 Policy_{i,t} + l_2 X_{it} + l_3 Price_{it} + l_4 Industry_{it} + l_5 Firm_{it} + l_6 Investment_{it} + l_7 Patent_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (11)$$

$$GTFP_{i,t} = m_0 + m_1 Policy_{i,t} + m_2 X_{it} + m_3 Price_{it} + m_4 Industry_{it} + m_5 IRIEC_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (12)$$

3.4.2 Estimating the indirect impacts of the land restriction policy on GTFP

We look for the productivity impacts of land restriction policy which exerts indirectly via the intermediary variables that we have supposed explaining the GTFP: land price, industry, and newly built enterprises, external investment, and patents for inventions or technological innovation (according to Table 1, line 2 and column 2). With the aim in view, we must estimate the impact of the “Policy” on these factors. We estimate separately the following equations such as:

$$Price_{i,t} = o_0 + o_1 Policy + o_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (13)$$

$$Industry_{i,t} = p_0 + p_1 Policy + p_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (14)$$

$$Firm_{i,t} = q_0 + q_1 Policy + q_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (15)$$

$$Investment_{i,t} = r_0 + r_1 Policy + r_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (16)$$

$$Patent_{i,t} = s_0 + s_1 Policy + s_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (17)$$

$$IRIEC_{i,t} = u_0 + u_1 Policy + u_2 X_{it} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (18)$$

The expected coefficients of o_1 and p_1 are positive, while the others are negatives. We can then calculate the indirect effects of the land restriction policy on GTFP as the sum of the products of Policy’s coefficient relative to each intermediary variable in equations 11 and 12, multiplied by its corresponding coefficient relative to Policy in equations 13 to 18 such as $l_3 o_1 + l_4 p_1 + l_5 q_1 + l_6 r_1 + l_7 s_1$ or $m_3 o_1 + m_4 p_1 + m_5 u_1$. In this way, we can evaluate precisely the contribution of each intermediary variable to the impact exerted by the Policy on GTFP.

3.4.3 Calculating the total impact of the land restriction policy on GTFP

Finally, the total effect of Policy is thus the sum of direct and indirect effects, which

$$l_1 + l_3 o_1 + l_4 p_1 + l_5 q_1 + l_6 r_1 + l_7 s_1, \quad m_1 + m_3 o_1 + m_4 p_1 + m_5 u_1$$

Table 1 summarizes the potential multiple effects that the land restriction policy is supposed to exert on GTFP in China’s cities. It distinguishes the direct effects of the land restriction policy from those passing through intermediary variables which are themselves affected by the land restriction policy. It shows that the effects of the land restriction policy on GTFP are positive either directly via its positive effect on allocation efficiency of land offer, or indirectly via its positive effects on price and transforming industrial structure in favor of tertiary industry, which in return influence positively GTFP. It shows finally that the effects of the land restriction policy on GTFP

are ambiguous, because the activities of firms, investment, invent and technological innovation may be friendly environmentally oriented or not.

Table 1: Expected impacts of land restriction policy on GTFP

Direct impacts	via management and allocation efficiency of land transfer		$Policy^+_{\rightarrow}GTFP$
Indirect effects via Transmission channels	Impacts of Policy on intermediary variables (a)	Impacts of intermediary variables on GTFP (b)	Impact of Policy on GTFP (c)=a*b
	$Policy^+_{\rightarrow}Land\ price$	$land\ price^+_{\rightarrow}GTFP$	$Policy^+_{\rightarrow}GTFP$
	$Policy^+_{\rightarrow}Industry$	$Industry^+_{\rightarrow}GTFP$	$Policy^+_{\rightarrow}GTFP$
	$Policy^-_{\rightarrow}firms$	$Firm^2_{\rightarrow}GTFP$	$Policy^2_{\rightarrow}GTFP$
	$Policy^-_{\rightarrow}Investment$	$Investment^2_{\rightarrow}GTFP$	$Policy^2_{\rightarrow}GTFP$
	$Policy^-_{\rightarrow}Invent$	$Invent^2_{\rightarrow}GTFP$	$Policy^2_{\rightarrow}GTFP$
	$Policy^-_{\rightarrow}Innovation$	$Innovation^2_{\rightarrow}GTFP$	$Policy^2_{\rightarrow}GTFP$
Total effects			$Policy^2_{\rightarrow}GTFP$

4. Empirical estimations

4.1 Sources and definitions of variables

To estimate the different impacts that the land restriction policy may exert on GTFP, this paper takes the Notice issued by the Ministry of Land and Resources in 2014 as a policy shock, regards the land restriction policy as a “quasi-natural experiment”, and constructs a Differences-in-Differences (DID) model to evaluate the impact. The cities with a resident population of more than 5 million after the implementation of the land restriction policy are thus considered as a treatment group, including Beijing, Tianjin, Shenyang, Shanghai, Nanjing, Hangzhou, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Dongguan, Chongqing, and Chengdu, a total of 14 cities. Among the 14 cities, the population of Hangzhou and Changsha exceeded 5 million for the first time in 2015 and 2017 respectively, so Hangzhou and Changsha have been included in the treatment group since 2015 and 2017 respectively. Other cities entered the treatment group in 2014. In addition to the treatment group, all prefecture-level cities are the control group of the empirical study. We define “Policy” as a dummy variable, which takes the value 1 if city i was subjected to the policy in year t , and 0 otherwise.

4.1.1 Data sources.

The data on land sales in the cities from 1999 to 2017 used in this paper are compiled from China Statistical Yearbook of Land and Resources. The demographic data used to determine the population of cities with more than 5 million people come from the Statistical Yearbook of Urban Construction in China as in Cheng et al. (2022). The annual energy data at provincial-level are from China Energy Statistics Yearbook, and are decomposed into cities level according to GDP shares. Carbon dioxide shadow price comes from Chen et al. (2020) who calculated city’s apparent CO₂ emission data. The technological innovation data comes from the Index of Regional Innovation and Entrepreneurship in China (IRIEC) published by the Peking University Enterprise Big Data Research Center in 2021. Finally, the data of the remaining variables are from the China Urban Statistical Yearbook.

4.1.2 Description of variables

(1) Dependent variable (GTFP) is measured by the Solow residual method, with

input factors including capital, labor, land, energy, and the shadow price of carbon dioxide to more accurately measures the high quality of the city's economic development.

Land, energy factors and shadow price of carbon dioxide are added as inputs into Cobb-Douglas production function such as:

$$Y_{i,t} = GFTP_{i,t} \times K_{i,t}^{\alpha_{K_{i,t}}} \times L_{i,t}^{\alpha_{L_{i,t}}} \times M_{i,t}^{\alpha_{M_{i,t}}} \times E_{i,t}^{\alpha_{E_{i,t}}} \times CP_{i,t}^{\alpha_{C_{i,t}}} \quad (19)$$

where $Y_{i,t}$ is the total economic output of the city i . $K_{i,t}^{\alpha_{K_{i,t}}}$, $L_{i,t}^{\alpha_{L_{i,t}}}$, $M_{i,t}^{\alpha_{M_{i,t}}}$, $E_{i,t}^{\alpha_{E_{i,t}}}$, $CP_{i,t}^{\alpha_{C_{i,t}}}$ are the inputs of capital, labor, land, energy factors and the shadow price of carbon dioxide for city i in year t . The parameters $\alpha_{K_{i,t}}$, $\alpha_{L_{i,t}}$, $\alpha_{M_{i,t}}$ and $\alpha_{E_{i,t}}$ are respectively the proportions of the contribution of capital, labor, land, and energy factors to the total economic output of city i in year t , and $\alpha_{C_{i,t}}$ is the special contribution ratio of the shadow price of carbon dioxide emissions to total economic output, reflecting the carbon emission constraint. According to the input factor substitution strategy, increasing capital investment for new energy technologies, carbon emission technologies, and energy efficiency improvement technologies can reduce CO₂ emissions.

Taking logarithms, equation (19) can be written as:

$$\ln Y_{i,t} = \ln GFTP_{i,t} + \alpha_{K_{i,t}} \ln K_{i,t} + \alpha_{L_{i,t}} \ln L_{i,t} + \alpha_{M_{i,t}} \ln M_{i,t} + \alpha_{E_{i,t}} \ln E_{i,t} + \alpha_{C_{i,t}} \ln CP_{i,t} \quad (20)$$

Thus, GTFP is the part of economic growth which cannot be attributed to capital, labor, land, and energy, as well as the special input factor of the shadow price of carbon dioxide (Del Gatto et al., 2011; Liu & Gong, 2022). It is used to estimate the impact of land restriction policy in this study.

The calculation of urban GTFP involves the following variables: ① Output variable, expressed as the real gross domestic product (GDP) of the city; ② Capital (K), calculated through the perpetual inventory method using city investment data; ③ Labor (L), expressed using the number of people employed at the end of the year in each city, calculated using the number of people working at the end of the period in the unit plus the private sector; ④ Land (M), using the area of the urban built-up area to express the number of land factor inputs, taking municipal district data as a proxy; ⑤ Energy (E), which refers to consumption of coal, coke, crude oil, gasoline, kerosene, diesel fuel, fuel, natural gas, electricity, etc. in total. Disaggregates total energy consumption data at the provincial level into cities by city GDP shares. ⑥ CO₂ shadow price, using urban CO₂ emissions data from Chen et al. (2020), defines the CO₂ shadow price as the additional investment cost required to reduce one unit of CO₂ emissions based on the input factor substitution strategy.

(2) Key explanatory variable (Policy) is the dummy variable of land restriction policy. 2014 is the time point of the policy, and the cities with population more than 5 million after the implementation of the land restriction policy are taken as the treatment group, and the rest of the cities are taken as the control group. Using the DID model, we explore the impact of the shock of the land restriction policy on the GTFP of cities.

(3) Control variables: ① GDP per capita ($\ln PGDP$), which represents city's actual GDP per capita and measures the level of the city's economic development; ② Road area per capita ($\ln Road$), which is actual road area in the end of the year and measures the level of the city's infrastructure; ③ Human capital level (Edu) is calculated as ratio of the city's number of general tertiary education students to the urban population; ④ Fiscal revenue ($\ln Rr_GDP$), share of real public revenues of real GDP to measure urban

local government revenues; ⑤ Foreign investment (*lnFDIK*) is a share of actual use of foreign capital in gross fixed capital formation in the current year; ⑥ Capital intensity (*lnKL*), using the ratio of the real capital stock to the number of laborers.

(4) Intermediary variables: ① Total area of land transferred (*lnLand*), measured by the total area of land transferred in the China Land and Resources Yearbook; ② Land price (*lnPrice*), measured by the transacted price of land transferred in the China Land and Resources Yearbook; ③ Upgrading of industrial structure (*Industry*), measured using the ratio of the tertiary sector's share of GRP to the secondary sector's share of GRP; ④ Newly built firms (*Firm*), using the score for the number of newly built firms in IRIEC; ⑤ Attracting external investment (*Investment*), using the score for attracting external investment in IRIEC; ⑥ Patents for inventions (*Invent*), using the score for invention patents in IRIEC; ⑦ Technological Innovation (*IRIEC*), using the aggregate index score in IRIEC.

All data involving price changes are price-deflated using 1999 as the base period. Variable definitions and sources are reported in Table 1A in Annex, while descriptive statistics are reported in Table 2.

Table 2
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>GTFP</i>	5231	0.422	0.270	-1.083	1.286
<i>Policy</i>	5390	0.010	0.098	0.000	1.000
<i>PGDP</i>	4799	24106.165	63295.245	77.276	4163697.000
<i>Road</i>	4735	1397.110	2022.854	1.000	21490.000
<i>Edu</i>	5177	0.014	0.020	0.000	0.131
<i>Rr_RGDP</i>	4812	622.783	401.849	8.564	16907.125
<i>FDIK</i>	5099	0.012	0.016	0.000	0.328
<i>KL</i>	5259	30.809	22.795	0.317	197.786
<i>Land</i>	6284	626.079	850.367	0.010	9086.840
<i>Addland</i>	4663	432.265	530.524	0.030	5788.560
<i>Price</i>	6282	563327.710	1541074.100	1.000	27182414.000
<i>Industry</i>	5297	0.873	0.454	0.094	9.482
<i>Firm</i>	6145	55.759	25.013	0.269	99.981
<i>Investment</i>	6145	57.672	22.835	6.356	99.981
<i>Invent</i>	6145	63.237	18.835	40.140	99.962
<i>IRIEC</i>	6145	57.405	24.262	0.240	99.942

4.2 The results of benchmark regressions

(1) Effects of the land restriction policy on land transfer. Table 3 reports the estimated results of Equation (1) in section 3. Column (1) reports the effect of the land restriction policy on the total land area of the urban land transfer. The estimated coefficient of "Policy" is negative (-0.415) and statistically significant at the level of 1%. This suggests that the land restriction policy has significantly reduced the total area of land transfer in megacities by about 41.5% on average per year. To further test the policy effect of this policy, column (2) of Table 3 reports the impact of the land restriction policy on the incremental total land area transferred in cities, which comes from the indicator of new construction land. The estimated coefficient of "Policy" is -0.477, and is statistically significant at the 1% level. This indicates that the land restriction policy has significantly reduced the incremental total land transfer area in megacities, and the policy reduces the incremental land transfer area in megacities by about 47.7% on average per year. Thus the land restriction policy significantly reduces the land supply of megacities mainly by reducing the new construction land. By reducing the new construction land, the restriction policy has protected arable land.

Table 3 Effects of Policy on land transfer

VARIABLES	(1) <i>lnLand</i>	(2) <i>lnAddland</i>
<i>Policy</i>	-0.415*** (-4.721)	-0.477*** (-3.172)
Constant	0.561 (1.053)	-3.865*** (-3.647)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Urban fixed effects	Yes	Yes
Observations	4,240	3,830
R-squared	0.796	0.687
r2_a	0.780	0.660
F	50.32	25.50

Note: *, **, *** represent statistics that are significant at the 10%, 5%, and 1% levels, respectively.

(2) Impacts of the land restriction policy on urban GTFP. Table 4 reports the results of the benchmark equations 2, 3 and 4 and all regressions are estimated with year and city fixed effects. Column (1) presents the regression results without control variables. The coefficient of “*Policy*” is estimated to 0.173 and statistically significant, indicating that the land restriction policy significantly increases GTFP in megacities. Column (2) presents the regression results with control variables. It shows that the coefficient of “*Policy*” is still statistically significant at the 1% level and positive (0.168), indicating that the land restriction policy has increased the GTFP of megacities by about 0.168 units on average per year compared to other cities. The obtained results preliminarily confirm that the land restriction policy has improved the allocation efficiency of urban land resources and promoted the sustainable development of the urban economy and environment. Column (3) adds total land transfer area to the baseline regression. It can be seen that the coefficient of total land transfer area (*lnLand*) is significantly negative. After adding the total land area transferred, the coefficients of the benchmark regression are still significant, but the coefficients become smaller. This indicates that the land restriction policy can indeed affect GTFP by reducing land transfer area, also accompanied by the effects of other mechanisms.

Table 4 Impact of the land restriction policy on urban GTFP

	(1) <i>GTFP</i>	(2) <i>GTFP</i>	(3) <i>GTFP</i>
<i>Policy</i>	0.173*** (8.096)	0.168*** (9.930)	0.160*** (9.416)
<i>lnPGDP</i>		0.129*** (13.920)	0.128*** (13.784)
<i>lnRoad</i>		-0.029*** (-4.941)	-0.029*** (-4.922)
<i>Edu</i>		1.256*** (4.912)	1.144*** (4.438)
<i>lnRr_RGDP</i>		-0.080*** (-11.957)	-0.082*** (-12.138)
<i>lnFDIK</i>		0.007*** (3.303)	0.007*** (3.412)
<i>lnKL</i>		0.034*** (5.764)	0.037*** (6.120)
<i>lnLand</i>			-0.013*** (-2.946)
<i>lnPrice</i>			0.013*** (3.337)
Constant	0.204*** (6.336)	-0.415*** (-3.934)	-0.490*** (-4.527)
Year fixed effects	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes
Observations	5,201	4,103	4,103

R-squared	0.767	0.846	0.847
r2_a	0.752	0.834	0.834
F	52.91	68.69	68.46

4.3 Impacts of the land restriction policy, intermediary variables on urban GTFP

The equations (5) to (10) are estimated to verify if intermediary variables are effectively transmission channels through which “Policy” influences GTFP.

4.3.1 Price mechanism

According to hypothesis 2 mentioned above, the land restriction policy may increase urban GTFP through the resource allocation effect of the price mechanism. To test this hypothesis, we first add land price (*lnPrice*) to the benchmark regression using equation (5). Column (1) of Table 5 reports the results of the land restriction policy affecting urban GTFP through the price mechanism. The results show that the estimated coefficient of *lnPrice* is significantly positive at the 10% level, with an estimated coefficient of 0.005. Column (1) of Table 7 reports the impact of the land restriction policy on urban land prices. The coefficient estimate of Policy is 0.416, which is significantly positive at the 1% level. This indicates that the land restriction policy significantly increases land prices in megacities, and the policy increases land prices in megacities by about 41.6% on average. The results show that the coefficient of land price is significantly positive and that the land restriction policy can promote urban GTFP through increasing land price. The possible explanation is that the land restriction policy increases the price of land, which can screen out efficient firms through the resource allocation effect of “the highest bidder wins” in the market. When firms are willing and able to buy land at higher prices, they are often high-quality firms. As a result, these high-quality enterprises expand their production after acquiring the land, with higher production efficiency and better technological research and development capabilities. The land restriction policy raises land prices and, by optimizing the allocation of resources, increase GTFP.

4.3.2 Industrial structural change

According to the hypothesis 3 mentioned above, the land restriction policy may increase the urban GTFP through industrial structural change in favor of tertiary industry. To test this hypothesis, we first add industrial structure change (*Industry*) to the benchmark regression using equation (6). Column (2) of Table 5 reports the impact of the land restriction policy on urban GTFP through industrial structure change. The results show that the estimated coefficient of *Industry* is significantly positive at the 1% level, with an estimated coefficient of 0.044. The estimated coefficient of land restriction policy on industrial structure change is 0.170 and statistically significant (Column (2), Table 7). This indicates that the land restriction policy promotes industrial structure change by facilitating the transformation of industrial structure from secondary industry to tertiary industry. This indicates that the land restriction policy can significantly enhance the urban GTFP through changing industrial structure. The possible reason is that the land restriction policy reduces the total amount of land supply so that industrial enterprises have to move to other cities or the tertiary industry. A reduction in the proportion of secondary industries and an increase in the proportion of tertiary industries in cities will reduce the energy consumption and environmental pollution of the city, and improve the GTFP.

4.3.3 Technological innovation

According to the hypothesis 4 mentioned above, the land restriction policy may reduce firms' technological innovation by decreasing new firms and external investment, this would dampen the GTFP of the city. To test this hypothesis, we add newly built firms (*Firm*), external investment (*Investment*), patents on inventions (*Invent*) and technological innovation (*IRIEC*) to the benchmark regression separately using equation (7) ~ (10). Columns (3) ~ (6) of Table 5 verifies the impact of the land restriction policy on GTFP by affecting newly built firms, external investment, patents on inventions, and technological innovation. The results show a decrease in the coefficient of urban GTFP compared to that of the benchmark regression. The coefficients of newly built firms, external investment, patents for inventions and technological innovation are all significantly negative at the 1% level. Columns (3) ~ (4) of Table 7 report the estimation results of the land restriction policy on newly built firms and attracting external investment. The results show that the Policy's estimated coefficients are -0.257 and -0.243, respectively, and both pass the significance test at the 1% level. This suggests that the implementation of the land restriction policies reduces newly built firms and external investment in land-restricted cities. What effect will this have on innovation? Column (5) of Table 7 examines the impact of the land restriction policy on patents on inventions (*Invent*) in cities. The results show that the coefficient of Policy is -0.187 and passes the significance test at the 1% level, suggesting that the land restriction policy inhibits the invention of patents in cities. Column (6) of Table 7 verifies the effect of land restriction policy on urban technological innovation (*IRIEC*), and the estimated value of Policy is -0.245 and significant at the 1% level. This indicates that the land restriction policy reduces the level of urban technological innovation.

The results indicate that the land restriction policy inhibits urban technological innovation, thus inhibiting the improvement of GTFP, and the negative impact of the land restriction policy on technological innovation is one of the mechanisms by which the land restriction policy affects GTFP. There may be two reasons for this phenomenon. Firstly, the reduction of land supply by the land restriction policy has led to the reduction of new investments and enterprises. Secondly, the land restriction policy has led to an increase in land price, and the increase in cost has prompted the transfer of secondary production to the outside. In this case, the implementation of the land restriction policy can lead to a decline in the level of urban innovation and inhibit the increase in GTFP.

Table 5

Mechanisms for the impact of the land restriction policy to increase GTFP

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>
<i>Policy</i>	0.166*** (9.786)	0.162*** (9.599)	0.140*** (8.052)	0.144*** (8.395)	0.137*** (8.056)	0.144*** (8.396)
<i>lnPGDP</i>	0.127*** (13.631)	0.141*** (14.875)	0.138*** (14.786)	0.134*** (14.487)	0.127*** (13.903)	0.135*** (14.582)
<i>lnRoad</i>	-0.030*** (-5.040)	-0.027*** (-4.508)	-0.028*** (-4.692)	-0.028*** (-4.791)	-0.024*** (-4.033)	-0.028*** (-4.771)
<i>Edu</i>	1.249*** (4.885)	0.990*** (3.818)	0.982*** (3.801)	0.973*** (3.765)	1.093*** (4.312)	1.009*** (3.925)
<i>lnRr_RGDP</i>	-0.082*** (-12.090)	-0.080*** (-11.966)	-0.077*** (-11.327)	-0.077*** (-11.324)	-0.081*** (-12.074)	-0.077*** (-11.372)
<i>lnFDIK</i>	0.006*** (3.227)	0.007*** (3.263)	0.007*** (3.684)	0.008*** (4.192)	0.006*** (2.917)	0.008*** (3.761)
<i>lnKL</i>	0.033*** (5.651)	0.037*** (6.314)	0.040*** (6.766)	0.041*** (6.823)	0.035*** (6.018)	0.040*** (6.705)
<i>lnPrice</i>	0.005*					

<i>Industry</i>	(1.808)	0.044***				
		(5.496)				
<i>Firm</i>			-0.002***			
			(-6.553)			
<i>Investment</i>				-0.002***		
				(-6.673)		
<i>Invent</i>					-0.003***	
					(-10.383)	
<i>IRIEC</i>						-0.002***
						(-7.217)
Constant	-0.453***	-0.671***	-0.364***	-0.346***	-0.192*	-0.358***
	(-4.214)	(-5.837)	(-3.443)	(-3.267)	(-1.805)	(-3.392)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,103	4,101	4,079	4,079	4,079	4,079
R-squared	0.846	0.847	0.848	0.848	0.850	0.848
r ² _a	0.834	0.835	0.836	0.836	0.838	0.836
F	68.52	69.04	69.48	69.51	70.87	69.67

4.3.4 Direct impacts of the land restriction policy on urban GTFP

As shown in Table 6, we validate the reliability of the intermediate them to the baseline regression. In fact, the coefficients of the intermediate variables are significant. Meanwhile, the coefficient of the key explanatory variable “*Policy*” becomes smaller as the added mechanism variables increase, but still statistically significant. This indicates that industrial structure upgrading, newly built firms, attracting external investment, invention patents, technological innovation, and land price are effectively the transmission channels through which the land restriction policy influences GTFP. The equations (11) and (12) are estimated and reported in Table 6, the coefficients of *Policy* in Columns (3) ~ (4) report the direct impacts of the land restriction policy on urban GTFP ($l_1=0.101$ or $m_3=0.135$). It is worth noting that technological innovation (*IREIC*) is the aggregate index that includes newly built firms, attracting external investment, invention patents. To avoid multiple covariance, it cannot be added to both the aggregate index and the sub-index in the regression.

Table 6

Direct impacts of the land restriction policy on GTFP

	(1)	(2)	(3)	(4)
	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>
<i>Policy</i>	0.166***	0.160***	0.101***	0.135***
	(9.786)	(9.440)	(5.756)	(7.883)
<i>lnPGDP</i>	0.127***	0.139***	0.143***	0.144***
	(13.631)	(14.597)	(15.179)	(15.162)
<i>lnRoad</i>	-0.030***	-0.027***	-0.022***	-0.026***
	(-5.040)	(-4.614)	(-3.689)	(-4.484)
<i>Edu</i>	1.249***	0.980***	0.552**	0.742***
	(4.885)	(3.779)	(2.127)	(2.851)
<i>lnRr_RGDP</i>	-0.082***	-0.082***	-0.077***	-0.078***
	(-12.090)	(-12.120)	(-11.572)	(-11.596)
<i>lnFDIK</i>	0.006***	0.006***	0.007***	0.007***
	(3.227)	(3.180)	(3.659)	(3.621)
<i>lnKL</i>	0.033***	0.036***	0.045***	0.042***
	(5.651)	(6.198)	(7.611)	(7.085)
<i>lnPrice</i>	0.005*	0.006**	0.008***	0.007**
	(1.808)	(1.976)	(2.959)	(2.465)
<i>Industry</i>		0.044***	0.034***	0.042***
		(5.552)	(4.316)	(5.339)
<i>Firm</i>			-0.001***	
			(-3.548)	
<i>Investment</i>			-0.001***	
			(-4.172)	
<i>Invent</i>			-0.002***	

			(-8.939)	-0.002***
<i>IRIEC</i>				(-7.237)
Constant	-0.453***	-0.715***	-0.415***	-0.658***
	(-4.214)	(-6.110)	(-3.504)	(-5.625)
Year fixed effects	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes
Observations	4,103	4,101	4,077	4,077
R-squared	0.846	0.847	0.853	0.850
r2_a	0.834	0.835	0.841	0.837
F	68.52	68.88	71.41	69.87

4.4. Indirect impacts of the land restriction policy on urban GTFP

The equations (13) ~ (18) are estimated to capture indirect impacts (Table 7). The statistically significant coefficient of “*Policy*” indicates that all identified intermediate variables such as *lnPrice*, *Industry*, *Firm*, *Investment*, *Invent* and *IRIEC* are effectively transmission channels through which the policy affects indirectly GTFP. As waited, the impact of “*Policy*” is positive for *lnPrice* and *Industry*, and negative for the others. Using Table 6 ~ 7, we can calculate the indirect effect of policy on urban GTFP through the mechanism variables. For example, the estimated impact of the policy on GTFP through price mechanism is about 0.003 (0.008*0.416). Likewise, through industrial structure transformation is about 0.006 (0.034*0.170), through newly built firms is about 0.0003 (-0.001*-0.257), through external investment is about 0.0002 (-0.001*-0.243), through patents on inventions is about 0.0004 (-0.002*-0.187), or through technological innovation is about 0.0005 (-0.002*-0.245). The indirect effects of *Policy* on GTFP are reported in Table 8.

Table 7 Estimation of the channeling variables of the land restriction policy on GTFP

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>lnPrice</i>	<i>Industry</i>	<i>Firm</i>	<i>Investment</i>	<i>Invent</i>	<i>IRIEC</i>
<i>Policy</i>	0.416***	0.170***	-0.257***	-0.243***	-0.187***	-0.245***
	(4.258)	(4.851)	(-11.311)	(-9.347)	(-10.096)	(-9.073)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,200	4,198	4,176	4,176	4,176	4,176
R-squared	0.900	0.796	0.895	0.848	0.866	0.847
r2_a	0.892	0.780	0.887	0.836	0.856	0.835
F	114.9	49.62	108.7	70.86	82.38	70.59

4.5 Total impact of the land restriction policy on GTFP

Calculation of the total effect of the land restriction policy on GTFP is given in Table 8. As it resorts from Table 7, the land restriction policy exerts a positive effect on Price and Industry, which themselves influence positively on GTFP; this leads to an impact of the of the land restriction policy which is equal to 0.003 and 0.006 for Price and Industry respectively (Table 8). Inversely the land restriction policy exerts a negative effect on *Firms*, *Investment*, *Invent* or *IRIEC*, which themselves influence negatively GTFP. Consequently, the indirect effects of the land restriction policy via *Firms*, *Investment*, *Invent* or *IRIEC* are positive, and equal respectively to 0.0003, 0.0002, 0.0004, or 0.0005 (Table 8). In summary, the total effect of the land restriction policy on GTFP is positive, either via its direct impacts, or via its intermediary variables; with direct impacts much higher than indirect effects.

Table 8 Impacts of land restriction policy on GTFP

Effects categories	Coefficients according to Eqs	Impacts
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Direct impacts - Firms, Investment, Invent or - IRIEC	l_1 m_1	0.101 0.135
Indirect effects - via Price - via Industry - via Firms - via Investment - via Invent or - via Price - via Industry - via IRIEC	l_{3o1} l_{4p1} l_{5q1} l_{6r1} l_{7s1} m_{3o1} m_{4p1} m_{5u1}	$0.034*0.17=0.006$ $-0.001*(-0.257)=0.0003$ $-0.001*(-0.243)=0.0002$ $-0.002*(-0.187)=0.0004$ $0.008*0.416=0.003$ $0.042*0.17=0.007$ $-0.002*(-0.245)=0.0005$ $0.007*0.416=0.003$
Total effects - firms, investment, patent or - IRIEC	$l_1+l_{3o1}+l_{4p1}+l_{5q1}+l_{6r1}+l_{7s1}$ $m_1+m_{3o1}+m_{4p1}+m_{5u1}$	0.11 0.15

Source: calculation of the authors from table 6 (columns 3 and 4) and according to Eqs (11) to (18)

5. Robustness tests

As mentioned above, the results of the benchmark regressions show the significant effects of the land restriction policy to urban GTFP. To check the validity of DID model, we firstly make parallel trend test, and Placebo testing. Secondly, to exclude the interference of other unobservable factors on the empirical results, we then conduct a series of robustness tests including sample data screening, excluding the interference of other policies, and propensity score-matching difference-in-difference (PSM-DID) analyses, to prove the reliability of our research conclusions. Finally, the heterogeneity analysis is made. The obtained results of these robustness tests confirm the stability of baseline results.

5.1 Parallel trend test

The parallel trend test is an important prerequisite for the construction of the DID model. It tests that the treatment and control groups selected for empirical evidence should be significantly different before the policy was implemented. Assuming the condition that the policy did not occur, the trend of the treatment and control groups over time should be the same. The ideal parallel trend test ensures that the effect obtained after double differencing between the treatment and control groups is a net effect from the policy and not an endogenous bias or interference from other factors. This paper thus uses the event study method proposed by Jacobson in 1993 for the parallel trend test, which can be expressed as follows:

$$GTFP_{i,t} = \alpha_3 + \sum_{t=-10}^3 \delta_t D_{i,t} + \lambda_3 X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t} \quad (21)$$

where $D_{i,t}$ is a dummy variable that is equal to 1 if city i implements a land restriction policy in year t , and otherwise, 0. Control variables are the same as in equation (3). This paper focuses on the coefficient δ_t , which captures the difference in GTFP between land-restricted cities and other cities. According to the theory of parallel

trend test, we expect that there would be no significant difference between the treatment group and the control group before the implementation of the land restriction policy. Figure 1 reports the parallel trend test plot obtained from the above equation.

Since the land restriction policy started in 2014 and our data only goes up to 2017, this paper reports results for the four years before the policy as well as the three years after the policy. This paper uses the year before the policy, i.e. 2013, as the base period. The results of the parallel trend test in Figure 1 show that the coefficients of the periods before the implementation of the land restriction policy are around 0. The results indicate that there is no significant difference between the treatment group and the control group before the implementation of the policy, and the study sample passes the parallel trend test. In addition, the coefficients of each period are significantly positive starting from the second period after the implementation of the land restriction policy. This indicates that the land restriction policy has a certain lag and effectively increases the GTFP of land-restricted cities after two years.

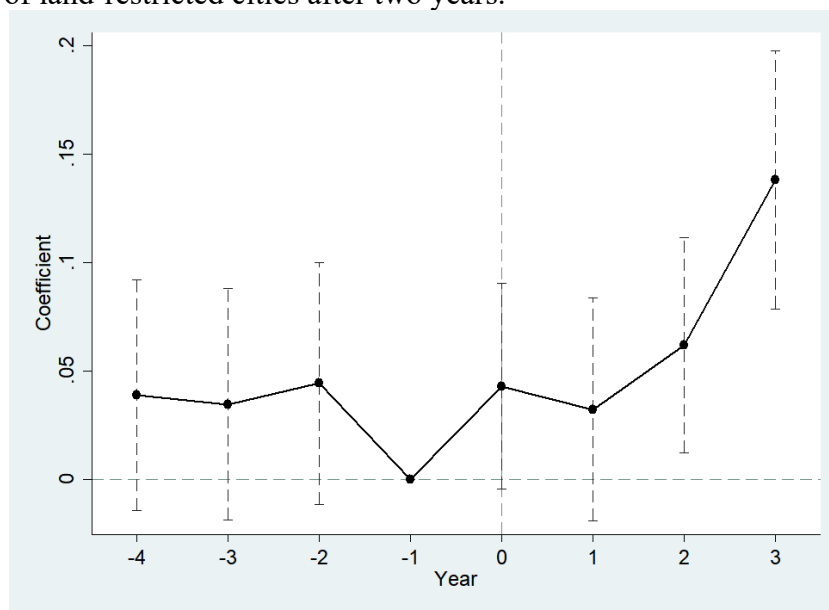


Figure 1 Parallel Trend Test Plot

Note: Solid dots indicate the estimated coefficients of δ_t in equation (21), and the short vertical lines are the 95% upper and lower confidence intervals corresponding to the robust standard errors clustered to the city level.

5.2. Placebo testing

To prove that the above empirically obtained conclusion that the land restriction policy increases urban GTFP is valid and not due to other unobservable factors, this paper conducts a placebo test. The result is tested to see if it is still significant by constructing a spurious model that is contrary to the facts. If the result obtained is still significant, then the result of the benchmark regression may be due to other unobservable factors and cannot be proved to be the effect of land restriction policy. As mentioned above, we would like the results obtained from the placebo test to be insignificant, thus counter-proving the reliability of the empirical results. We used two different placebo tests, a time placebo test, and a city placebo test.

(1) Time placebo test.

Time placebo test verifies the reliability of the empirical results by constructing a false policy time. In this paper, we advance the implementation time of the land restriction policy by 5 years, 4 years, 3 years, and 2 years, respectively, to construct the false policy time, which is denoted by *Policyfalse1*, *Policyfalse2*, *Policyfalse3*, and

Policyfalse4, and substitute them into equation (4) to conduct the regressions. The results reported in Table 4 show that the regression coefficients for *Policyfalse1*, *Policyfalse2*, *Policyfalse3*, and *Policyfalse4* are not significant, and the placebo test for constructing a false policy time passes. This indicates that the results of the benchmark regression are not due to random time shocks but due to the implementation of the land restriction policy, proving the reliability of the conclusion that the land restriction policy significantly increases urban GTFP.

Table 9 Time placebo test results

	(1) 5 years in advance <i>GTFP</i>	(2) 4 years in advance <i>GTFP</i>	(3) 3 years in advance <i>GTFP</i>	(4) 2 years in advance <i>GTFP</i>
<i>Policyfalse1</i>	0.015 (1.016)			
<i>Policyfalse2</i>		-0.012 (-0.838)		
<i>Policyfalse3</i>			-0.010 (-0.705)	
<i>Policyfalse4</i>				-0.010 (-0.684)
Constant	-0.059 (-0.299)	-0.061 (-0.309)	-0.060 (-0.303)	-0.061 (-0.305)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes
Observations	4,275	4,275	4,275	4,275
R-squared	0.898	0.898	0.898	0.898
r2_a	0.891	0.891	0.891	0.891
F	113.2	113.2	113.2	113.2

(2) Urban placebo test.

City placebo test to test the reliability of the empirical results by constructing a spurious treatment group of cities. Since there are only 14 cities in the treatment group implementing the land restriction policy, this paper randomly selects 14 cities in the sample cities as the fake treatment group cities and the rest of the cities as the fake control group cities. Substituting them into equation (4) for the regression, the coefficients of the impact of implementing the land restriction policy of urban placebo on urban GTFP are estimated. Due to the small sample size of the treatment group, we repeated the above random selection process 400 times to obtain 400 regression coefficients and their corresponding p-values. Figure 2 plots the p-values and kernel density distributions of these 400 coefficient estimates. It can be seen that the regression coefficients fall around the value of 0 and follow a normal distribution, with the vast majority of regression coefficients being insignificant. In addition, the coefficient on the baseline regression is 0.168, which lies outside the plot of spurious regression coefficients and is an impossible event in the urban placebo test. Accordingly, it can be ruled out that the results of the benchmark regression are caused by unobservable factors in the city, but due to the implementation of land restriction policy. This again proves the reliability of the empirical results.

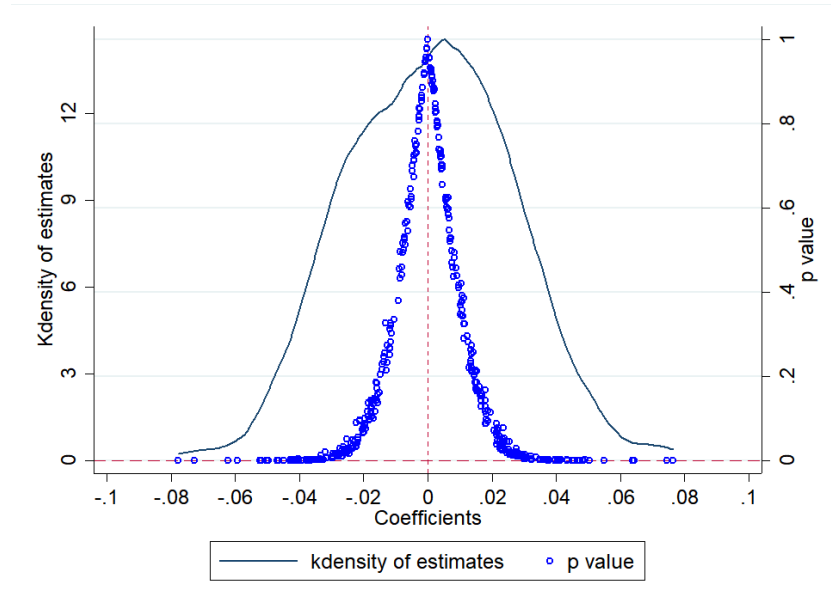


Figure 2 Urban placebo test plot

(1) Sample data screening.

To avoid bias in the results due to extreme values, we re-regressed equation (4) after truncating the within-sample dependent variable *GTFP* by 1% and 5%, respectively, and the regression results are shown in columns (1) and (2), Table 10. It can be seen that the regression coefficients of the core explanatory variable, *Policy*, are significantly positive at the 1% level regardless of whether *GTFP* is truncated at 1% or 5%. This is similar to that of the baseline regression, proving that our findings are still robust after removing the effects of extreme values.

Table 10 Regression results for 1% and 5% truncated

VARIABLES	(1) Truncated 1% <i>GTFP</i>	(2) Truncated 5% <i>GTFP</i>
<i>Policy</i>	0.157*** (8.896)	0.147*** (7.948)
Constant	-0.522*** (-5.014)	-0.580*** (-5.595)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Urban fixed effects	Yes	Yes
Observations	4,058	3,822
R-squared	0.839	0.807
r2_a	0.825	0.790
F	64.34	49.49

(2) Exclusion of interference from other policies.

To avoid other policies during the sample period that would affect urban *GTFP* and cause bias in the benchmark regression, this study combed through other relevant policies during the land restriction policy period that might affect urban *GTFP*. Those include the dual-control zone policy put forward by the nationally-introduced Air Pollution Prevention and Control Law, the National Development and Reform Commission's Circular on the Pilot Work of Promoting National Innovative Cities, and the Announcement on the Implementation of Special Emission Limits for Air Pollutants. To avoid the impact of the above policies on the results of the benchmark regression,

we add dummy variables for the above policies to the benchmark regression to exclude the impact of these policies. Among them, *ShuangKong* is a dummy variable indicating whether the city is a dual-control zone in that year, taking 1 if it is and 0 otherwise. *Innov_Pilot* is a dummy variable indicating whether the city is an innovation pilot city in that year, taking 1 if it is and 0 otherwise. *Atmos* is a dummy variable indicating whether the city is an air pollution control zone in that year, taking 1 if it is and 0 otherwise. *Lowcarb_Pilot* is a dummy variable indicating whether the city is an air pollution control zone in that year, taking 1 if it is and 0 otherwise.

The results are shown in Table 11, where columns (1) ~ (4) demonstrate the regression results excluding the interference of dual-control policies, innovative city pilots, air pollution control zones, and low-carbon city pilot policies, respectively. The coefficients of the core explanatory variable *Policy* can be seen that, after excluding the disturbances from the four policies mentioned above, the coefficients of *Policy* pass the test of significance at the 1% level. These are consistent with the results of the benchmark regression, proving that the benchmark regression results are still robust after excluding the interference of other policies. It is worth noting that the coefficient of air pollution control zones is negative in the regressions that include the land restriction policy. This could be due to overly stringent environmental regulation policies having a direct negative impact on firm performance and that the negative effect of the cost of following environmental regulation policies outweighs the positive effect indirectly generated by incentives to innovate (Lanoie et al., 2011). This also confirms the “cost of compliance argument”.

Table 11 Regression results excluding other policy disturbances

	(1) Dual-control zone policy <i>GTFP</i>	(2) Pilot Innovative Cities <i>GTFP</i>	(3) Air pollution control zone <i>GTFP</i>	(4) Low-carbon city pilot <i>GTFP</i>
<i>Policy</i>	0.168*** (9.930)	0.158*** (9.222)	0.170*** (9.264)	0.157*** (9.280)
<i>ShuangKong</i>	0.111* (1.779)			
<i>Innov_Pilot</i>		0.028*** (3.373)		
<i>Atmos</i>			-0.004 (-0.342)	
<i>Lowcarb_Pilot</i>				0.037*** (5.552)
Constant	-0.526*** (-4.566)	-0.436*** (-4.129)	-0.412*** (-3.899)	-0.418*** (-3.981)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes
Observations	4,103	4,103	4,103	4,103
R-squared	0.846	0.847	0.846	0.847
r2_a	0.834	0.834	0.834	0.835
F	68.69	68.69	68.45	69.10

(3) PSM-DID model.

To avoid selection bias and endogeneity problems that may exist in the study sample, we further adapted the PSM-DID model to validate the reliability of our findings. The PSM-DID model combines the propensity score matching method (PSM) and the DID model, which effectively solves the possible selectivity bias between the treatment and control groups and endogeneity issues, resulting in credible causal effect estimates.

Table 12 reports the regression results for PSM-DID. Columns (1), (2), (3), and (4)

report the regression results using nearest neighbor matching, radius matching, kernel matching, and Mahalanobis matching, respectively. It can be seen that the coefficients of the core explanatory variable *Policy* all pass the significance test at the 1% level and that the results of several matching methods are very similar and largely consistent with the results of the benchmark regression in Table 4. This further suggests that the land restriction policy can significantly contribute to urban GTFP.

Table 12 PSM-DID regression results

	(1)	(2)	(3)	(4)
	Nearest neighbor matching	Radius matching	Kernel matching	Mahalanobis matching
	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>
<i>Policy</i>	0.167*** (10.471)	0.170*** (10.595)	0.167*** (10.471)	0.168*** (9.930)
Constant	-0.162 (-1.326)	-0.167 (-1.368)	-0.162 (-1.326)	-0.415*** (-3.934)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes
Observations	3,162	3,158	3,162	4,103
R-squared	0.864	0.864	0.864	0.846
r2_a	0.851	0.850	0.851	0.834
F	62.59	62.36	62.59	68.69

5.3 Heterogeneity analysis

5.3.1 Impact of the land restriction policy on GTFP in different economic regions

To explore the possible different effects of the land restriction policy on urban GTFP according to the cities' location, we test the heterogeneity by dividing China into eastern, central, and western regions. Eastern region includes nine land-restricted cities, namely Beijing, Tianjin, Shenyang, Shanghai, Nanjing, Hangzhou, Guangzhou, Shenzhen, and Dongguan. Central region includes three land-restricted cities, namely Zhengzhou, Wuhan, and Changsha. Western region includes two land-restricted cities, Chongqing and Chengdu. The obtained results reported in columns (1) ~ (3) of Table 13 shows that the coefficients of *Policy* are all significantly positive. The coefficient of the eastern region is the largest, and the land restriction policy promotes the GTFP in the eastern region by 0.167 units. The coefficient for the western region is the smallest and passes the test of significance only at the 10% level. The higher level of economic development of the cities in the eastern and central regions makes them more capable to improve their high-energy-consuming and high-polluting production through industrial structure upgrading and green technological innovations to increase GTFP.

5.3.2 Impact of the land restriction policy on GTFP in different levels of cities

Differences in the city's level may also make the impact of land restriction policy on the city's GTFP different. For this reason, we divided Chinese cities into municipalities, provincial capitals, and prefecture-level cities according to their city administrative levels. The regression results are shown in column (4) ~ (6) of Table 13. It can be seen that the coefficients of *Policy* are all significantly positive. The results show that the land restriction policy promotes GTFP best for municipalities, second best for prefecture-level cities, and least for provincial capitals. This is because municipalities are the centers of economic development and have a high concentration of population. There are also preferential treatment of political resources. These make it more advantageous for municipalities to upgrade their industrial structure and make technological innovations. Moreover, compared with provincial capitals, prefecture-level cities have greater development potential. They are in a critical period of industrial structural transformation, coupled with the "latecomer's advantage", so that the land

restriction policy has a better effect on the improvement of GTFP than that of provincial capitals.

5.3.3 Impact of the land restriction policy on GTFP in cities with different resource endowments

The core purpose of the land restriction policy is to prevent the over-exploitation of urban land and to guard the red line of arable land. In practice, resource cities and non-resource cities face different pressures in the implementation of land restriction policy in different cities due to different resource types, resource endowments, and utilization degrees, and the effectiveness of its implementation may be significantly different. To verify whether there would be a difference in the green development driving effect of the land restriction policy on resource cities and non-resource cities, this paper further divided the sample cities into resource cities and non-resource cities for comparative analyses based on the divisions of the “National Sustainable Development Plan for Resource Cities (2013-2020)”. The regression results are shown in Table 12, which shows that the coefficient of the explanatory variable *Policy* is positive and passes the test at the 1% significance level for both resource and non-resource cities, while the coefficient of resource cities is slightly larger than that of non-resource cities. This indicates that the effect of land restriction policy on GTFP enhancement in resource cities is about 43.56% higher than that in non-resource cities during the sample period. This may be because the development of resource cities depends on local natural resources, and the implementation of the land restriction policy will have a more direct impact on resource cities. This can force them to transform their traditional polluting industries, upgrade their green innovation technologies, and increase the GTFP.

Table 13 Heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Eastern	Central	Western	Municipalities	Provincial capitals	Prefecture-level cities	Resource cities	Non-resource cities
	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>	<i>GTFP</i>
<i>Policy</i>	0.167** *	0.150** *	0.089*	0.809** *	0.084** *	0.183** *	0.145** *	0.101** *
Constant	(8.645) 0.576** *	(3.997) - 1.394** *	(1.720) - 1.012** *	(10.210) 5.712** *	(3.981) - 1.391** *	(4.129) - 0.499** *	(3.306) 0.421	(9.648) 0.057
Control variables	(3.324) Yes	(-7.295) Yes	(-5.375) Yes	(6.014) Yes	(-4.138) Yes	(-4.833) Yes	(1.534) Yes	(0.315) Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,560	1,513	1,030	63	400	3,640	1,634	2,489
R-squared	0.826	0.793	0.819	0.981	0.937	0.828	0.921	0.950
r ² _a	0.811	0.775	0.799	0.969	0.929	0.814	0.913	0.946
F	55.98	43.75	41.09	82.53	111.4	59.24	121.2	221.9

6. Conclusions: economic and political implications

In this paper, we take the land restriction policy implanted in the Chinese megacities since 2014 as a “quasi-natural experiment” to assess its different impacts on urban GTFP. A DID model is proposed and applied to urban panel data over the 1999-2017 period for 14 cities affected by the land restriction policy. A series of robustness

tests are carried out.

We find that the land restriction policy ①has significantly reduced the total land transfer area of the megacities by 41.5% on average per year compared with other cities; ②has increased the urban GTFP by about 0.168 units on average per year compared with other cities; ③has indirectly improved the urban GTFP via rising land prices and transforming industrial structure from secondary to tertiary industry, which themselves affect positively GTFP; ④via its negative effects on technological innovation by reducing the number of newly built firms, investment and patents of invention in lands restricted cities, which influence themselves negatively GTFP.

These results suggest that the land restriction policy has promoted the sustainable development of the urban economy in favor of environment, but with a risk of urban green desindustrialization. To mitigate this risk, a selective industrial land supply in big cities should be adopted in favor of enterprises in the field of green technological innovation by granting land and subsidizing the land price, and thus enhance the GTFP.

Finally, it is interesting to extend this study by using a recent period to overcome the short period of the land restriction policy from 2014 to 2017. It is also interesting to find out a micro firm data to study the specific impact of the policy on the firms.

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Annexes

Table 1A
Definitions and sources of variables

Variable names	Notation	Description of definitions
Green total factor productivity	<i>GTFP</i>	Urban GTFP is calculated by OP and LP methods, while adding capital, labor, land, energy, and shadow prices of carbon dioxide to production function
Land restriction policy	<i>Policy</i>	If the city is subject to the land restriction policy in the current year, Policy is equal to 1; otherwise, Policy is 0
GDP per capita	<i>lnPGDP</i>	The logarithm of per capita GDP
Level of human capital	<i>Edu</i>	The ratio of the number of students of ordinary colleges and universities to the household registered population at the end of the year
Level of fiscal revenue	<i>lnRr_GDP</i>	The logarithm of citywide real public revenues as a share of real GDP
Foreign investment	<i>lnFDIK</i>	The logarithm of the city's actual amount of foreign investment used in the year as a share of gross fixed capital formation
Capital intensity	<i>lnKL</i>	The logarithm of the ratio of the real capital stock to the number of workers
Total area of land transferred	<i>lnLand</i>	The logarithm of total land area transferred
Total area of land transferred added	<i>lnAdland</i>	The logarithm of the total new land transfer area
Land price	<i>lnPrice</i>	The logarithm of the land transfer transaction prices
Upgrading of industrial structure	<i>Industry</i>	The ratio of the city's tertiary sector to the secondary sector's share of GRP
Newly built firms	<i>Firm</i>	Score for the number of newly built firms in IRIEC
Attracting external investment	<i>Investment</i>	Score for attracting external investment in IRIEC
Patents for inventions	<i>Invent</i>	Score for invention patents in IRIEC
Technological innovation	<i>IRIEC</i>	Aggregate index score in IRIEC