LOW-RISE BUILDINGS IN BIG CITIES: THEORY AND EVIDENCE FROM CHINA*

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This Version: 4 July 2022

* I am grateful to Christian Hilber and Felipe Carozzi for their continuous guidance and support. I thank Gabriel Ahlfeldt, Paul Cheshire, Steve Gibbons, Laurent Gobillon, Gianluca Marcato, Lu Han, Vernon Henderson, Mathias Hoffmann, Cameron LaPoint, Max Nathan, Luca Repetto, Filipa Sa, Clara Santamaría, Marta Santamaria, Olmo Silva, Yanos Zylberberg, as well as participants at the 2020 Virtual Meeting of the Urban Economics Association, University of Zurich, LSE, UCLA, and University of Reading for comments and suggestions. All errors are the sole responsibility of the author. Address correspondence to: Xiaolun Yu, University of Reading, Henley Business School, Reading RG6 6UD, United Kingdom. Phone: +44-07541-640-381. E-mail: xiaolun.yu@henley.reading.ac.uk.

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Abstract

Land use regulations have been implemented around the world and have economic consequences beyond housing markets. However, few studies have investigated these regulations in the context of developing countries. This paper sets out to understand the determinants of floor area ratio (FAR) limit — a major form of land use regulation that specifies construction density — in China. I first develop a spatial equilibrium framework that assumes that local governments set FAR limits such as to maximize endogenous local population size. Designing a higher FAR limit enables them to supply more housings and public goods but also increases negative externalities caused by density. I show that in equilibrium, local governments with higher budgetary revenue opt to set lower FAR limits to reduce negative externalities and attract more population. I then employ a rich dataset of over 200,000 residential land transactions in China and a panel of counties to perform empirical analysis. Exploiting the exogenous variation generated by a central government administrative adjustment policy, I find that a one standard deviation increase in local government budgetary revenue decreases FAR limits by 0.6. Quantitative analysis then suggests that the impact of Chinese 'Land Finance Model' on local FAR design is significant and contributes to the country's housing affordability problem.

JEL classification: G28, H72, R21, R28, R31, R38.

Keywords: Land use regulation, floor area ratio, housing supply, political economy in China, spatial inequality

1. Introduction

Land use regulation has been a long-time focus of economic research. It is imposed in every country in the world with a variety of forms such as zoning in the US and green belt in the UK. The literature suggests that land use regulation has a wide range of economic impacts on housing markets, labour supply, and local environment (*e.g.*, Mayer and Somerville 2000, Glaeser and Kahn 2004, Mills 2005, Saks 2008, Gyourko and Molloy 2015, Hilber and Vermeulen 2016, Gyourko and Krimmel 2021). Previous studies also find that land use regulation is determined by the incentives and actions of agents in local communities. Homeowners, politicians, and developers all participate in the designation process, and restrictive land use regulation is implemented to protect home value, reduce local dis-amenities, prevent low-income households from moving in, and maintain local fiscal advantage (Fischel 1987, Bates and Santerre 1994, Pogodzinski and Sass 1994, Glaeser and Ward 2009, Hilber and Robert-Nicoud 2013, Been *et al.* 2014). However, the literature to date contains few attempts on investigating land use regulation in the context of developing countries. This is largely due to a vague understanding of local politics and a lack of comprehensive datasets in these economies.

This paper sets out to understand the determinants of land use regulation in China, a developing country that experiences a rapid process of urbanization during the past decades.[1] I investigate the designation process of floor area ratio (FAR) limit, a major form of land use regulation that specifies construction density in China. FAR limit regulates the maximum ratio of the floor area within the proposed property relative to the size of the land parcel. It has a crucial impact on land value and housing supply, as it determines the number of dwellings to be built out by developers. Besides, FAR limit also affects neighbourhood environment and amenities, as high construction and population densities are always associated with negative externalities such as less sunshine, more congestion, and more pollution (Duranton and Turner 2018, Borck and Schrauth 2019, Carozzi and Roth 2020). Understanding the determinants of FAR limits could thus provide meaningful insights into house price dynamics and urban environment.

Exploring the process of FAR design also has important policy implications. Between 2005 and 2017, the mean value of the FAR limit for residential use is much lower in superstar cities such as Shanghai (1.42) and Beijing (2.28) compared with the national mean level (2.85) in China.[2] This is contradicted with the common view that superstar cities build out high-rise buildings and benefit from the agglomeration economies. Conversely, cities in the less developed middle and western regions set relatively high FAR limits for residential use, while these cities are not experiencing economic prosperity as Beijing and Shanghai. As a result, high-rise buildings are constructed and then left vacant in some cities, which is widely covered by the media as the 'ghost town' phenomenon in China.

To understand the determinants of FAR limits, I first develop a spatial equilibrium framework which includes households, developers, and local officials. Households migrate across cities

[1] The share of the urbanized population in China rises from 25.8% in 1990 to 57.4% in 2017 (National Bureau of Statistics in China).
[2] Estimates using this paper's baseline sample. See section 3.1 for details.

with no cost to achieve the maximized utility level, and developers bid for land plots for new construction. Local governments design the optimal FAR limit to maximize population size. The model implies that in spatial equilibrium, the optimal FAR design is the outcome of local governments trading-off between the benefits (more housing supply, land revenue, and public good provision) and the costs (negative externalities to local amenities) of high construction density. Local governments with sufficient budgetary revenue are less relied on land sales to finance public good provision and opt to set relatively low FAR limits to attract population and reduce the negative externalities caused by density. Conversely, cities with fewer budgetary revenue are more financially relied on land sales and would design higher FAR limits to generate more fiscal income. The theoretical framework also shows that the Chinese land finance model contributes to the spatial differences in FAR design and the housing affordability issues in some major cities.

I then exploit a comprehensive dataset of over 200,000 residential land transactions in China between 2005 and 2017 and a county-level panel to empirically estimate the impact of local budgetary revenue on FAR design. Budgetary revenue is a commonly used measure of local fiscal capacity in China and includes local fiscal revenues such as taxes, administration fees, and the shared profits from state-owned enterprises. The aim of the empirical analysis is to test for the theoretical framework's main proposition on the determinants of FAR limits. To mitigate the endogeneity concerns of reverse causality and local confounding characteristics, I create 3km × 3km spatial grids across the country and compare land parcels within a small geographic unit. I then exploit the exogenous variation generated by a central government administrative adjustment policy for identification. The policy turns self-governed counties into prefecture-governed districts, which breaks administrative boundaries, leads to infrastructure improvement, and boosts local agglomeration economy and budgetary revenue. To mitigate the concern of selection bias, I utilize a propensity score matching (PSM) approach to compare cities that are economically similar. In line with the theoretical framework's prediction, this paper's more credible PSM-IV estimate suggests that a one standard deviation increase in local budgetary revenue will decrease FAR limit by 0.6, which is 44% of the standard deviation of the FAR limit in the baseline sample. The main estimation results are robust after I utilize a spatial boundary design and a placebo test with 1,000 randomly generated treatment dates to address the concerns of unobserved local characteristics and the spurious documentation of the treatment effect. Finally, a quantitative analysis is conducted and shows that the Chinese land finance model contributes to the country's spatial difference in land use regulations and housing affordability issues.

This paper relates to the literature that explores the economics of land use regulations, including the welfare analysis of land use regulations (Cheshire and Sheppard 2002, Turner *et al.* 2014), the determinants of housing supply restrictions (Glaeser and Ward 2009, Saiz 2010, Hilber and Robert-Nicoud 2013, Been *et al.* 2014) and the consequences (Mayer and Somerville 2000, Gyourko and Molloy 2015, Hilber and Vermeulen 2016). Previous studies have mainly discussed land use regulations in the context of developed countries. A predominant theory proposes that homeowners (or 'not in my backyard residents', NIMBYs) oppose local new developments and vote for politicians who can introduce restrictive land use regulations to protect their home value. The literature also discusses the fiscal incentive (Rolleston 1987, Bates and Santerre 1994) and the exclusion incentive (Pogodzinski and Sass 1994) of restrictive land use regulations. This paper contributes to the literature by documenting the determinants of land use regulation in the context of a developing country. Theoretically, this paper links the Rosen-Roback spatial equilibrium framework with the politician tournament theory in China (Li and Zhou 2005) and discusses how local officials' incentive and the Chinese 'Land Finance Model' influence land use design. Empirically, previous studies mainly measure land use regulations that are aggregated at some geographical levels (*e.g.*, The Wharton Residential Land Use Regulatory Index). This paper uses a unique and comprehensive dataset of individual land transactions in China to measure time-varying regulatory restrictiveness at the land plot level with detailed land parcel information. The micro-level dataset also allows me to conduct different identification strategies and I find robust results.

This paper also relates to the literature on the economics of construction density control in the contexts of both developed countries (Barr 2013, Ahlfeldt and McMillen 2018) and developing countries (Fu and Somerville 2001). Cai, Wang, and Zhang (2017) estimate a dataset of land parcels matched with residential projects and find that developers tend to violate FAR restrictions in more desirable locations in China. Brueckner *et al.* (2017) show that the elasticity of land price with respect to the FAR limit could be a measure of local regulation stringency. Using a national sample, they estimate the elasticity to be city-specific, which shows variation in the stringency of FAR regulation across Chinese cities. However, the literature to date contains few attempts on understanding the determinants of these density control regulations, and this paper aims to fill the gap.

This paper also refers to the discussion of urban density, agglomeration, and negative externalities. While density leads to higher productivity (Duranton and Puga 2014), it also causes air pollution (Carozzi and Roth 2020) and potential damage to the ecosystem (Glaeser and Kahn 2004). This paper contributes to the literature by providing an original political economy story on how local governments trade-off between the benefits and the costs of construction density control to achieve a desirable outcome.

In the end, this paper relates to the literature on Chinese economy including fiscal policies and fiscal decentralization (Jin *et al.* 2005, Han and Kung 2015), urban expansion and career incentive of city leaders (Wang *et al.* 2019), and risks of housing markets in China (Wu *et al.* 2012, Wu *et al.* 2016). This paper contributes to the literature by studying how local governments design land use regulations under the Chinese fiscal system and thus enriches the discussion on local public finance and housing markets in China.

The rest of this paper is structured as follows. Section 2 describes the local fiscal system and land use regulation design in China and provides a theoretical framework to guide the empirical analysis. Section 3 contains the data sources, descriptive statistics, identification strategy, and empirical results. Section 4 presents robustness checks for these findings and additional results. Section 5 concludes.

2. Background and Theoretical Framework

2.1. Institutional Background

2.1.1. Local Fiscal System and Land Auction Market in China

During the past decades, China has experienced several waves of reforms with the aim of fiscal decentralization. Fiscal decentralization was first accomplished in the early 1980s through a fiscal contract system. Under this system, local governments could keep almost all extra revenues generated beyond their pre-set contract responsibilities. Following a major tax reform in 1994, which weakened the budgetary revenue for local governments, and a major housing reform in 1998, city leaders learned that selling land leases was an effective way to generate fiscal revenue. Land revenue has since then become a key feature of local public finance in China (Cao *et al.* 2008). It is classified as 'extrabudgetary revenue' and local governments are not required to share it with the central government. Over the past decades, local governments have increasingly relied on selling land parcels as a major source of fiscal revenue to finance local public goods and infrastructure investments. As shown in Figure 1, land sale revenue equals between 36% and 65% of local government's budgetary revenue in China from 2003 to 2017. Budgetary revenue is a commonly used measure of local fiscal capacity in China and includes local taxes, administration fees, and the shared profits from state-owned enterprises, but it doesn't include land sale revenue. Figure 1 also shows that if the 'indirect' land revenue such as the land appreciation tax is considered, the aggregated land revenue will even exceed local government's budgetary revenue in 2010.

By law, all urban lands are owned by the state in China. Since 1988, the prefecture land bureau has gotten the authority to allocate the use rights of vacant urban lands. The maximum terms of the land use rights are 70 years for residential use, 50 years for industrial use and mixed use, and 40 years for commercial use. In 1990s, most land leases were allocated through negotiation between local governments and developers. In order to control for the corruption occurred during negotiation, the Ministry of National Land and Resources banned negotiated land deals after August 2004. Since then, all urban land leases for private development have been allocated through public auctions. Land auctions are held by local government's land bureau, and detailed information of land parcels are required to be available to the public. According to Cai, Henderson, and Zhang (2013), more than 95% of land auctions were conducted via either English auctions or two-stage auctions. Local governments collect land revenue from these auctions and the land sale serves as an important source of local fiscal revenue besides taxes and administrative fees.

2.1.2. FAR Design and The Objective of Local Officials

Local government's urban planning bureau designs land use regulations such as FAR limit and the share of green area for each land plot to be released. These plots will then be turned over to the land bureau for auction. In practice, based on local governments' documentations and my interviews with local officials and developers, the designation process of FAR limit is mainly through the discussions and negotiations between county-level governments and prefecture-level governments. County-level governments propose land use plans to the prefecture-level governments, and the decisions will be made by prefecture-level governments based on different environmental, economic, and urban planning criteria. This paper uses the county-level budgetary revenue in the main empirical analysis because county-level governments, especially the more rural ones ('xian'), usually have a major influence on land use regulation design. This paper also applies the prefecture-level budgetary revenue as a robustness check and the results are reported in the appendix.

Local governments design both an upper bound and a lower bound for FAR limit. This paper defines FAR restriction as the upper bound constraint because the upper limit is always binding in practice and lower bound cases are very rare (Cai *et al.* 2017).

Local governments consider different factors when designing FAR limit: First, high construction density could increase the output of housing units upon the same land plot, leading to more supply and more affordable housing. Second, high FAR limit can significantly increase the value of land plot, as developers are allowed to build out and sell more housing units. Figure 2 plots the linear correlation between FAR upper limit and land price per square meter using over 200,000 residential land transactions in China and presents a clear positive association between FAR limit and land value. In a similar vein, figure 3 shows the quadratic correlation between FAR limit and land value and suggests that although FAR limit could increase land value, the marginal increase will decrease as FAR limit increases.[3] Since land sale revenue serves as a crucial source of fiscal revenue for many local governments, higher FAR design enables them to collect more fiscal revenue for local public good provision and infrastructure investment. Third, high construction density also has negative impacts on local environment and amenities. For instance, residents in the lower floors of a high-rise building need to bear with bad view and less sunshine. High construction density will also reduce the proportion of the land plot being developed into green spaces. Besides, high-rise buildings will accommodate dense population, which leads to more congestion and pollution. Figure 4 presents an example of the negative externalities caused by construction density using over 39,000 residential projects in China. Figure 4 shows that residential projects with higher FAR limits are more likely to have lower green ratios, meaning that the larger concrete construction area will take up more space for green spaces and therefore influence neighbourhood environment and reduce the value of local amenities.

Local governments trade-off between the benefits and the costs of high FAR design to achieve their objectives. City leaders in China have an incentive to pursue for economic growth during their term time. Li and Zhou (2005) find that local officials are more likely to be promoted if provinces experience economic prosperity under their governance. As land sale accounts for a significant proportion of local fiscal revenue, if local leaders only care about raising fiscal revenue to invest in infrastructure projects and boost local GDP, they will design FAR limit as high as the developer's optimal construction density to maximize land value. Figures 5 and 6 report the average budgetary revenue per person and the average FAR limit (weighted by land plot size) for residential use at the prefecture level in China, respectively. Figure 5 illustrates that cities along the southeast coast have more budgetary revenue compared with the inland cities, as these cities are more economically developed and attract more high-technology companies and high-skilled labours. Figure 6 then shows that cities along the southeast coast tend to design lower FAR limits for residential use, and cities in the less developed central and western regions set higher FAR limits. Figures 5 and 6 together suggest that at least in the more

[3] This is in line with the expectation that the marginal construction cost will increase as building height increases. I will also discuss this stylized fact in the theoretical framework.

economically advanced coastal cities, local officials consider factors more than just maximizing land sale revenue when designing FAR limits. If local governments could collect sufficient fiscal revenue from other sources, they tend to design relatively low-rise buildings. To understand the designation process of FAR limits and the trade-off faced by local governments, I propose a spatial equilibrium model and the details are discussed below.

2.2. Theoretical Framework

In this sub-section, I develop a static spatial equilibrium model of local governments, households, and developers to guide the empirical analysis. The model illustrates how local governments trade-off between the benefits and the costs of high FAR design. The model is built on the spatial equilibrium framework developed by Rosen (1979), Roback (1982), and Diamond (2017), and I extend the classic framework by introducing the political incentive of local officials in China (Li and Zhou 2005). The set of players and the timing of the game are as follows: local governments simultaneously choose a FAR limit, sell land parcels to developers, and spend all fiscal revenue including budgetary revenue and land revenue on the provision of local public goods. Households then make location decision among cities based on their expected utility level and the payoffs are realized. In the end, the urban system reaches a spatial equilibrium, and households settle in one city and have no incentive to move.

Households

Suppose that there is an urban system which consists of multiple cities. Homogenous households with wage w can move across cities with no migration cost and make their location decision based on the expected utility level. Household's utility is determined by the consumption of housing h, the consumption of tradable goods c, public goods g provided by local government, and local amenities θ. Suppose that p represents housing price per square meter. A Cobb-Douglas type utility function and household's budget constraint are as below:

$$U = h^{\alpha} c^{1-\alpha} g^{\beta} \theta$$

$$s.t. \quad w = ph + c$$

Where $0 < \alpha < 1$ and $0 < \beta < 1$. To maximize individual utility level, each household will consume housing h and tradable goods c as below:

$$\frac{h}{c} = \frac{\alpha}{1-\alpha}$$

Let d denote housing stock of a city with population L, and suppose that local government releases N land parcels with size S and FAR upper limit f to the housing market. Under the assumption of housing market clearing:

$$hL = NSf + d$$

Housing price p, housing consumption h, and tradable good consumption c are thus determined as below:

$$h = \frac{NSf+d}{L}, \; c = \frac{1-\alpha}{\alpha}\left(\frac{NSf+d}{L}\right)$$

$$p = \frac{wL}{NSf + d} - \frac{1-\alpha}{\alpha}$$

Land Markets and Developers

Suppose that identical developers purchase land parcels from the local government. Let r denote the land price per square meter and $c(f)$ denote the construction cost per square meter. $c(f)$ is a convex function with respect to f ($c'(f) > 0, c''(f) > 0$) because the marginal construction cost will increase as the building height increases. Developers bid for land parcels based on their expected house price p_e and the construction cost $c(f)$. After acquiring land plots, developers will build projects with construction density f.[4] Developer's profit π_d is thus given by:

$$\pi_d = Sfp_e - Sr - Sc(f)$$

Under the assumption of perfect competition and free entry and exit, developers make zero profit and land price r is given by:

$$r = fp_e - c(f)$$

Suppose that housing market is clear before local government releasing any new land parcels. Let d denote housing stock and L_0 denote local population before land release. Total housing demand equals total housing supply:

$$q_0 L_0 = d$$

Developers expect house price p_e to be at the same level as what they observe before any new land plot is released. The expected housing price p_e and land price r are determined as below:

$$p_e = \frac{wL_0}{d} - \frac{1-\alpha}{\alpha}$$

$$r = \frac{wL_0}{d} f - \frac{1-\alpha}{\alpha} f - c(f)$$

This paper assumes that r is an increasing and concave function with respect to f ($\frac{\partial r}{\partial f} > 0, \frac{\partial^2 r}{\partial^2 f} < 0$), meaning that FAR limit has a positive impact on land price per square meter, but the marginal effect is decreasing as FAR limit increases.[5] as FAR limit increases, developers can build and sell more housing units, so FAR limit is likely to have a positive impact on land value. However, land value will not increase infinitely because construction cost $c(f)$ will also increase with the building height. This paper's assumption is in line with previous findings on

[4] This assumption is in line with Cai, Wang, and Zhang (2017)'s finding that the upper FAR limits are always binding for residential projects in China.

[5] $\frac{\partial r}{\partial f} = \frac{wL_0}{d} - \frac{1-\beta}{\beta} - c'(f)$ and $\frac{\partial^2 r}{\partial^2 f} = -c''(f)$. It is easy to prove that $\frac{\partial^2 r}{\partial^2 f} < 0$. This paper assumes that $\frac{wL_0}{d} - \frac{1-\beta}{\beta} - c'(f) > 0$ so that $\frac{\partial r}{\partial f} > 0$. The assumption about land value is also in line with the findings of Figure 3.

the positive correlation between FAR limits and land value (Brueckner *et al.* 2017) and on the binding FAR upper limits (Cai *et al.* 2017).[6]

Negative Externalities

High population density is associated with negative externalities such as congestion and pollution (Duranton and Turner 2018, Borck and Schrauth 2019, Carozzi and Roth 2020). Higher construction density f also leads to worse views and less sunshine. These negative externalities will adversely affect local amenities θ.

Let $\frac{NSf+d}{NS+S_0}$ denote the overall construction density within a city, where S_0 denotes the land area of housing stock d, and NS denotes the area of new land supply. $\theta(\frac{NSf+d}{NS+S_0})$ denotes the amenity value considering all the negative externalities caused by density and is defined as a convex function with respect to f (therefore, $\frac{\partial\theta(\frac{NSf+d}{NS+S_0})}{\partial f} < 0, \frac{\partial^2\theta(\frac{NSf+d}{NS+S_0})}{\partial^2 f} < 0$). I simplify $\theta(\frac{NSf+d}{NS+S_0})$ to θ because all the parameters other than f in this function are exogenously determined.

Local Officials Design the Optimal FAR Limits

Suppose that local government simultaneously designs FAR limit f for N land parcels with size S and sell them to developers. Local government then spends all fiscal revenue including land sales NSr and budgetary revenue B on public good provision. Budgetary revenue B includes local taxes and administrative fees and is first treated as exogenous in the model.[7]

This paper assumes that the provision of public good g follows a simple production function with government's labour input normalized to 1 and productivity A:

$$g = A(NSr + B)$$

Households make location choices based on their expected utility level. Under the assumption of housing market clearing:

$$U = \frac{\overbrace{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}(NSf+d)}^{\textit{supply effect}}}{L} \overbrace{A(NSr+B)^{\beta}}^{\textit{fiscal effect}} \overbrace{\theta}^{\textit{externality effect}}$$

The equation above illustrates the benefits and costs of high FAR limits from the perspective of household's utility. First, when local government sets higher FAR limits, there will be more supply of housing units, which bring down housing price and increase the quantities of housing consumed by households (supply effect). Second, higher FAR limits generate more land sale revenue and enable local governments to provide more public goods (fiscal effect). Third, there is a negative externality effect associated with construction density, which will adversely influence the value of local amenities. If local government behaves as a benevolent social

[6] Table A3 provides empirical evidence about the positive correlation between land price per square meter and FAR upper limit, especially for residential use, using land transaction data in China.
[7] In the future, I plan to discuss the endogenized budgetary revenue B.

planner and only cares about local resident's utility level, they will set the optimal FAR limit at a point where the benefits and the costs have the largest gap.

This paper assumes an 'open city' scenario, meaning that households can move freely across cities to achieve the highest utility level and there is no migration cost. When the urban system reaches a spatial equilibrium, every household will have the same utility $\overline{U}$ and no incentive to move out. The population L within a city is thus endogenously determined as follow:

$$\overline{U} = \frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}(NSf + d)}{L} A(NSr + B)^{\beta}\theta$$

$$L = \frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}(NSf + d)A(NSr + B)^{\beta}\theta}{\overline{U}}$$

The equation above suggests that the population size within a city will increase if there are more housing supply and public goods and will decrease if there are more negative externalities caused by density.

The 'politician tournament theory' (Li and Zhou 2005) proposes that local leaders in China are incentivised to boost local economy as their probabilities of being promoted will increase if local GDP increases rapidly under their governance. This paper thus assumes the optimal FAR limit f^* for local officials could maximize the aggregate economic output as well as the population size L[8] within a city:

$$f^* = \underset{f}{arg\,max}\,(L)$$

This paper then proves the following inequality:[9]

$$\frac{\partial f^*}{\partial B} < 0$$

This inequality illustrates the main proposition to be tested in this paper:

Proposition – Local governments with more budgetary revenue opt to design lower FAR limits in order to reduce the negative externalities caused by density and to maximize local population size, as they could collect sufficient fiscal revenues from other sources.

The Consequence of Land Finance Model

How will local officials design FAR limits if the land finance model is abolished, meaning that local governments don't reply on land sales to finance public goods. Under this scenario, local government will only spend budgetary revenue B on local public good provision and the population size in spatial equilibrium will be determined by the following equation:

[8] The objective of local officials to increase population size is supported by the competition among local governments to attract young talents in China ('qiang ren da zhan'). Local governments provide a series of benefits to undergraduates and postgraduates who decide to settle in. These benefits include a relaxation of the hukou requirements and local housing subsidies.

[9] See proof in Appendix C.

$$L = \frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}(NSf + d)AB^{\beta}\theta}{\bar{U}}$$

Suppose that local governments design the optimal FAR limit f^* to maximize population size L. It is easy to prove that:[10]

$$\frac{\partial f^*}{\partial B} = 0$$

This equation suggests that under the scenario when the land finance model is abolished, the optimal FAR limit f^*will not be influenced by local budgetary revenue B anymore. In fact, it will only be determined by the trade-off between the additional housing supply caused by high-rise buildings and more negative externalities caused by higher construction densities. Under the scenario when land sale revenue is not a major fiscal source of local governments, the difference in local budgetary revenue will not influence FAR design. To quantify the impact of land finance model on land use regulation design, this paper will conduct a quantitative exercise in the empirical analysis based on the predictions from the main specification.

Simulations

In this sub-section, I visualize the main proposition of the theoretical framework by assuming different values for the parameters in the model and running simulations.

Figure 7 plots the relationship between city population size and FAR design under the main scenario. Suppose that there are two cities A and B, and the only difference between these two cities is that city A has a higher budgetary revenue. All the three curves for city A in Figure 7 present how the population size of city A will change given city A and city B's FAR design under the spatial equilibrium. Figure 7 shows that there always exists a same optimal FAR limit for city A to maximize local population size regardless of the FAR design of city B. In a similar vein, all the three curves for city B present how the population of city B will change depending on FAR design, and there always exists a same optimal FAR limit for city B to maximize local population.

Figure 7 also presents how the optimal FAR design will differ as local budgetary revenue changes. The optimal FAR limit for the poorer city B is always higher than the optimal FAR limit for the richer city A, which is in line with the main proposition that higher local budgetary revenue leads to lower FAR design. As rich cities could collect sufficient budgetary revenue from sources other than land sales to finance local public goods, the marginal fiscal benefit of high FAR design will be relatively small, and they are more likely to design relatively low FAR limits to reduce the negative externalities caused by density and to attract more population.

In addition, Figure 8 plots the relationship between population size and FAR design under the scenario when the land finance model is abolished. In this case, cities will finance public goods only using local budgetary revenue. Figure 8 shows that if local governments are not financially relied on land sales, the optimal FAR limits for city A and city B will always be the same regardless of local budgetary revenue. This is also in line with the theoretical framework's

[10] See proof in Appendix C.

prediction, as under this scenario, there is no substitution between budgetary revenue and land sales for public good provision, and the optimal FAR level is determined by the trade-off between additional housing supply and negative externalities. This paper will quantify the impact of land finance model on FAR design in the empirical analysis.

3. Empirical Analysis

3.1. Data and Descriptive Statistics

This paper's main estimation sample uses 202,816 residential land transactions in 281 prefecture-level cities and 1,804 counties in China from 2005 to 2017. The data source is the official website of China land market, which covers the vast majority of land transactions in China. The main dataset records detailed information at the plot level including land transaction price, address, the date of transaction, the upper and lower limits of FAR, the type of land use, a land quality evaluated by government, land area, planned total floor area, the type of auction, land use, and the land bidder. This paper defines FAR restriction as the upper bound of the FAR limit, because the cases of lower bound constraints are very rare, and the upper limit is almost always binding (Cai, Wang, and Zhang 2017). I use Gaode Map API to geo-code all the land parcels based on their location information. As Figure 9 shows, the geocoded land parcels cover most major cities in the country. Besides, the land parcels are widely spread within cities. For instance, Figure 10 presents a rich amount of geocoded land transactions both in the central area and at the urban fringe of Beijing.

This paper first identifies the land use of each plot based on its planning description and then selects residential land transactions for the main empirical analysis. Residential land sale serves as the major source of land revenue and accounts for over 75% of all the land sales in this paper's estimation sample. Wang, Zhang, and Zhou (2019) also document that about three quarters of the land sale revenue created through public auctions come from the sale of residential land. This paper estimates a sample including commercial and industrial lands and the results are reported in the appendix.

As discussed before, I utilize a spatial grid approach to control for time-invariant local characteristics. I create a fishnet that covers all the land transactions in the baseline sample and the size of each grid is 3km × 3km. Figure 10 shows the spatial grids in Beijing. By controlling for grid fixed effects in the main specification, this paper compares land parcels within relatively small geographical areas and mitigates the concern of unobserved time-invariant local features such as historical construction density, geographical obstacles, and local amenities.

This paper collects nation-level, prefecture-level, and county-level characteristics from different sources including China Financial Statistical Yearbook, China Financial Statistics of Cities and Counties, City Statistical Yearbook, local statistical yearbooks, and local government statistical reports. The administrative adjustment records are collected from the Ministry of Civil Affairs. I merge the land parcel data with the county-level and prefecture-level panels to construct the baseline estimation sample. Following the literature, I dropped the top 1% and the bottom 1% of observations in terms of FAR restriction to mitigate the bias caused by extreme values. The key explanatory variable, budgetary revenue of local government, is standardised so that I can easily interpret the estimated coefficients. This paper subtracts the sample mean of budgetary revenue from itself and divide this difference by the standard deviation. This transformation allows me to interpret the estimated coefficient as an increase in the FAR limit due to a one standard deviation increase or decrease in local budgetary revenue. This paper also collects station-level air quality data from China National Environmental Monitoring Centre.

Basic summary statistics computed for a sample of residential land transactions in China from 2005 to 2017 are detailed in Panel A of Table 1. There are in total 202,816 residential land transactions. The average value of the land transaction price is 53 million RMB (around 6 million GBP[11]), and the average size of the land parcel is 25,000 square meters. The key land use regulation explored in this paper, FAR upper limit, has a mean value of 2.8 and a standard deviation of 1.4. Most land parcels have FAR restrictions between 1 and 6, and there is significant bunching at round numbers. The mean value of distance to CBD is 42 km. Panels B and C of Table 1 then shows the descriptive statistics for city-level and county-level characteristics from 2005 to 2017, respectively. The key explanatory variable in the empirical analysis, budgetary revenue at the county level, has a mean value of 1,313 million RMB.

Figures 6 and 7 present the spatial patterns of local budgetary revenue and FAR design at the prefecture level in China, respectively. Figure 6 suggests that regional core cities and cities along the southeast coast tend to have more budgetary revenue. These cities, including Tier 1 cities such as Beijing and Shanghai, are reckoned as the more economically advanced cities. Conversely, Figure 7 presents the average FAR limit for residential use and shows a reverse spatial pattern. I compute the weighted average FAR limit[12] at the prefecture level using residential land plots between 2005 and 2017, and the map suggests that regional core cities and cities along the southeast coast tend to set relatively low FAR limits for residential use. Figures 6 and 7 together suggest that cities with more budgetary revenue tend to design lower FAR limits. This stylized fact based on raw data is in line with the main proposition from the theoretical framework.

3.2. Empirical Specifications and Identification Strategy

3.2.1. Main Specification and Endogeneity Concerns

This paper's empirical strategy is designed to test for the main proposition in the theoretical framework and explore the determinants of FAR limits in China using land transaction data. I first estimate the following equation using OLS:

$$FAR_{icdgym} = \phi_d + \rho_g + \beta Budget_{dy} + \delta_{ym} + \gamma' X_i + \tau' Z_{cy} + \varepsilon_{icdgym} \tag{1}$$

where i indexes individual land parcel, y indexes transaction year, and m indexes transaction month. The key explanatory variable, $Budget_{dy}$, represents the budgetary revenue of county d in year y. A vector of county fixed effects is represented by ϕ_d and a vector of spatial grid fixed effects is represented by ρ_g. δ_{ym} is a set of time dummies (year-month fixed effects) and X_i is a set of land parcel controls including land area, distance to CBD, a land quality measured

[11] Based on the currency exchange rate in November 2020.
[12] The average FAR limit is weighted by the size of each land plot.

by government, the type of land auction, and the longitude and latitude of the land plot.[13] Z_{cy} is a set of prefecture-level time-varying characteristics including population, average salary, local industry composition, the number of universities and the number of hospitals in city c in year y. This paper estimates this equation by OLS, clustering standard errors at the grid level to account for potential spatial autocorrelation in FAR design and local housing market conditions. The parameter of interest is β, measuring the impact of local budgetary revenue on FAR restriction. This paper also estimates a similar specification as equation (1) but replaces county-level budgetary revenue with prefecture-level budgetary revenue to test if the impact is robust using the local fiscal measure at a higher administration level.

One important caveat with the OLS estimates of equation (1) is that the explanatory variable $Budget_{dy}$ is likely endogenously determined, causing the estimate to be biased. There are two major concerns. First, since FAR limit is correlated with land value, and certain types of local taxes such as land appreciation tax and stamp duty are computed based on land price, FAR limit is likely to have a direct effect on local government's budgetary revenue, which leads to reverse causality. This simultaneity issue will underestimate the negative impact of local budgetary revenue on FAR limit.[14] Second, unobserved local features might cause bias in the OLS estimate. For instance, the population density in the pre-existing informal housing upon the land plot will increase the resettlement costs for land acquisition (Fu and Somerville, 2001), and local governments might design high FAR limits to compensate for the increasing acquisition costs. Meanwhile, the literature suggests that there is a positive impact of informal housing on accommodating migrant inflows within cities (Niu *et al.* 2020), so the density of informal housing might have a positive effect on local budgetary revenue. This confounding factor is not fully controlled for in the main specification due to data availability and will underestimate the negative effect of budgetary revenue on FAR limits.[15] Besides, the literature suggests that there is a significant amount of corruption in the land auction market in China (Cai, Henderson, and Zhang 2013), and the time-varying local corruption level might be correlated with both FAR design and budgetary revenue. Lastly, previous research suggests that land use regulations tend to be historically dependent: if there are many low-rise buildings within a neighbourhood, local officials are more likely to design low FAR limit for a newly released land parcel there.

3.2.2. Identification Strategy

To address the endogeneity concerns as discussed above, this paper first creates 3km × 3km spatial grids covering the whole country and applies a grid fixed effect strategy to compare land parcels within a small geographic unit. This method allows me to control for time-invariant local features such as historical construction density and geographical obstacles. Because of the rich land transactions in the sample, I can observe sufficient variations in FAR limits after controlling for the grid fixed effects. I also control for the effect of county-level time-invariant features and macro trends by including county fixed effects and year-month fixed effects, respectively. To mitigate the concern of high-skilled labour sorting into superstar cities, I

[13] I control for the longitude and latitude of each land plot to take into account the requirement of sunshine time for buildings, as locations in different longitudes and latitudes have different sunshine angles and exposure.
[14] See proof in Appendix D.
[15] See proof in Appendix D.

control for time-varying local income level and amenities such as average salary, industry composition, the numbers of universities and medical facilities.

However, two potential endogeneity issues remain after I control for multiple fixed effects and the time-varying local characteristics: First, FAR limit is likely to be correlated with local budgetary revenue through taxes related to land value. Second, unobserved time-varying local factors such as corruption and the density of informal housing are likely to affect both FAR design and budgetary revenue.

To address these endogeneity concerns, this paper proposes an instrument variable strategy by exploiting the exogenous variation generated from a central government administrative adjustment policy named ‘Turning Counties into Districts’ (TCID). The details of this policy are discussed as below.

China has established a unitary centralized power system since 1949. The system of Chinese local administrative division has four levels (from top to bottom): provincial-level, prefecture-level (city-level), county-level, and town-level. As shown in Figure 11, the county-level administration consists of municipal districts, which are more urban and directly governed by prefecture-level governments, and counties, which are more rural and have a higher degree of administrative autonomy in different aspects such as fiscal budget and land supply. This administrative autonomy introduces more flexibility for county leaders to adjust policies based on local economic conditions. However, it also causes administrative boundaries and inefficiencies among different levels of governments. For instance, if a prefecture government wants to implement a city-wide subway network, the county government might oppose and delay this project because the subway station will generate noise and pollution to the county residents.

During the past decades, there is a rapid process of urbanization in China, and many rural counties have been turned into municipal districts to be directly governed by the prefecture-level governments. The major aim of the TCID policy is to boost local economic development by breaking administrative boundaries and promoting cooperation among different levels of governments. In most cases, the TCID policy is conducted following the steps as below: prefecture-level governments first investigate the counties to be adjusted and cooperate with county-level governments to prepare for an administrative adjustment proposal. They then submit the proposal to the provincial government and the state council (the central government). The central government reviews the adjustment plan and make their policy decision based on a variety of local economic and social conditions. In 1993, the ministry of civil affairs from the state council published the criteria that both the prefecture and the county to be adjusted need to satisfy to get the approval of TCID. The criteria include the lower limit of population, the upper limit of employment in the agricultural sector, and some requirements on urban expansion, local budgetary revenue, and industry composition.

From 2000 to 2019, 105 prefecture-level cities in China have turned their counties into municipal districts. As Figure 12 shows, there are two major waves of the administrative adjustments, starting in the early 2000s and the early 2010s respectively. While the first wave is largely driven by central government’s instruction, the second wave mainly reflects the demand from the local government side. During the second wave, prefectures actively apply for turning their counties into municipal districts to avoid geographical and administrative obstacles for future urban development. Figure 13 shows a substantial spatial variation in cities that implemented the TCID adjustments between 2000 and 2019. Figure 14 then presents an example of the TCID policy. In June 2002, a prefecture-level city Xi'an got the approval that its Chang'an county (one of the light blue polygons) could be turned into a municipal district (dark blue polygon). After this adjustment, Chang'an district would be directly governed by the prefecture-level government.

The impacts of the TCID policy have been widely discussed. TCID policy usually benefits the prefecture-level government by bringing in extra fiscal revenue from the county-level administration and allowing the prefecture to implement city-wide infrastructure projects. For instance, Foshan turned 4 of its counties into municipal districts in 2002. After the administrative adjustment, Foshan government spent 10 billion RMB on an infrastructure project to connect the 4 newly adjusted municipal districts with the pre-existing central districts. This project significantly reduced transportation costs and led to an industry upgrading in the pre-existing municipal districts because high-skilled workers and high-end industries would concentrate in the central area after all districts were well connected.

However, the TCID policy seems to be a double-edged sword for the rural county to be adjusted. On one hand, the county can benefit from having access to the prefecture-level public goods after the adjustment. On the other hand, the county needs to transfer a large proportion of its fiscal revenue to the prefecture-level government and might compromise to the prefecture-level infrastructure plan. Some county residents are worried that after the TCID policy, more resources will be reallocated from the newly adjusted districts to the pre-existing central districts, because the prefecture officials might have a preference on the central area. Figure 9 presents the night lights in Xi'an before and after the TCID policy, respectively. The figure shows that although the newly adjusted Chang'an district were more urbanized after the TCID policy, the nightlight in the pre-existing central municipal districts became much brighter after the adjustment. This paper assumes that the TCID policy will generate an exogenous increase in the pre-existing central district's budgetary revenue due to the infrastructure improvement, industry upgrading, and the growing agglomeration economies after the adjustment.

Figure 13 shows that the administrative adjustments are widely implemented across Chinese cities and provides sufficient spatial variations for the empirical analysis. The identification assumption is that pre-existing central municipal districts are likely to be the 'winner' of this policy and can collect more budgetary revenue after the adjustment, because TCID policy breaks administrative boundaries and stimulates infrastructure improvement in the centre area. Meanwhile, there is no direct correlation between local FAR design and the implementation of TCID policy, as the adjustment decision is based on certain criteria set by the central government and not likely to be influenced by local land use regulations. The administrative adjustment might directly influence land plots within the newly adjusted districts because these districts will be governed by the prefecture-level government with a different planning idea. This paper thus removes all the 'new districts' in the estimation sample and the treatment group will only include the land plots within the pre-existing central municipal districts. This paper then estimates the following first stage regression:

$$Budget_{dy} = \beta TCID_d \times Post_y + Controls + \varepsilon_{dy} \quad (2)$$

where d indexes individual county/district and y indexes year. The instrument, $TCID_d \times Post_y$ is an indicator variable that takes the value of 1 if d is a pre-existing municipal district within a prefecture that gets the TCID approval and y is after the implementation of the administrative adjustment in the prefecture. I then follow a two-stage-least-square (2SLS) strategy to estimate the impact of the budgetary revenue on FAR design using the budgetary revenue variable instrumented with the TCID policy.

For the instrumental variable estimator to be consistent and unbiased, the conditions are as below: First, the TCID policy affects local budgetary revenue directly (relevance). Second, the treatment is as good as randomly assigned (independence). Third, the policy influences FAR design only through changes in local budgetary revenue (exclusion restriction). This paper proves the instrument relevance by reporting both the first-stage results and the F-statistics. Although Figure 13 presents substantial spatial variations in the TCID adjustments across Chinese cities, it is challenging to ensure both independence and exclusion restriction. This paper argues that the TCID policy does not have a direct correlation with local FAR design because the policy decision is based on certain criteria set by the central government. However, there is an obvious concern about the potential selection bias of the treated cities. Prefectures can get the TCID approvals because these cities are experiencing a rapid process of urbanization and can meet the criteria set by the central government. Some unobserved local trends during the urbanization process might be correlated with both local FAR design and the TCID policy. To address this concern, this paper applies a propensity score matching (PSM) approach. I first estimate a city's propensity to be treated using a logit regression with explanatory variables including the population, population growth rate, industry composition, GDP per capita, and budgetary revenue, which are the criteria that central government uses to evaluate local government's application for the administrative adjustment. Next, I select one counterfactual city in the same year with the propensity score closest to the treated city. These matched cities offer a counterfactual urbanization path for how the treated cities would have experienced, had they not been approved to have the administrative adjustment. From estimating the PSM sample, this paper can mitigate the concern of selection bias and compare cities experiencing similar urbanization process before the TCID policy.

One might argue that even the PSM sample is selected based on the observed local characteristics, and there is still a concern of unobserved local features. I mitigate this concern by using a spatial boundary design and selecting land plots within 5 km away from county boundaries. Land plots close to county boundaries tend to have similar neighbourhood and are highly comparable. This paper then uses these land plots to estimate the impact of local budgetary revenue on FAR design and the results are reported in section 4.

3.3. Main Results

Table 2 summarizes the results from estimating equation (1) using a sample of residential land transactions in China between 2005 and 2017. Additional covariates are included into the estimation sequentially.

Columns (1) to (3) in Panel A report the naïve OLS estimates. Column (1) controls for land parcel characteristics, year-month fixed effects, and county fixed effects. Column (2) includes the spatial grid fixed effects, and column (3) further controls for a vector of time-varying prefecture-level characteristics such as population, industry composition, and average salary. The standard errors in all specifications are clustered at the grid level to allow for a degree of spatial autocorrelation. Columns (1) to (3) show that budgetary revenue has a negative impact on FAR design, and all estimates are statistically significant at 1% level. To quantify the results, the estimate from column (3) suggests that a one standard deviation increase in county-level budgetary revenue will decrease FAR limit by 0.08, which is around 6% of the standard deviation of FAR limits in the baseline sample. The negative coefficient from the OLS specification is in line with proposition (1) that local governments with more budgetary revenue opt to design lower FAR limits.

As discussed in section 3.2.1, potential endogeneity issues might lead to biased OLS estimates. This paper then applies the instrumental variable strategy to study the impact of budgetary revenue on FAR design and the IV results are reported in Panel B of Table 2. All the coefficients have the expected signs and are statistically significant at 1% level. The more credible IV estimate in column (3) suggests that a one standard deviation increase in local budgetary revenue will decrease FAR limit by 0.6, which is around 43% of the standard deviation of the FAR limit in the baseline sample. The IV estimates are larger than the OLS estimates in Panel A, which is in line with the expectation that reverse causality and unobserved confounding factors will underestimate the negative impact of budgetary revenue on FAR design.

Regarding the validity of the instrument, the Kleibergen-Paap F statistics in Panel B of Table 2 suggest that weak instrument is not a concern. In addition, Panel C of Table 2 reports the first-stage estimation results. The coefficients from columns (1) to (3) are all positive and statistically significant, meaning that as expected, the TCID policy will increase the budgetary revenue of the pre-existing municipal districts.

A PSM-IV method is then applied to mitigate the concern of potential selection bias. Table 3 compares different variables between the treated and the control cities before and after the propensity score matching, respectively. The table shows that there is a significant difference between the treated and the control cities before the propensity score matching: cities that get the TCID approval usually have more population and higher budgetary revenue. These cities are more likely to experience a rapid process of urbanization, which leads to potential selection bias. Table 3 then shows that after the propensity score matching, the treated and the control cities are well balanced regarding different characteristics, either used or not used in the matching, as T statistics are insignificant for all variables. Therefore, cities in the PSM sample are likely to experience a similar urbanization process and more comparable for the empirical analysis.

Figure 15 illustrates the average budgetary revenue for the treated and the control districts before and after the propensity score matching. Most cities in my estimation sample have implemented the TCID after 2010, and Panel A presents a clear gap in local budgetary revenue between the treated and control groups prior to 2010. This leads to the selection concern that cities getting TCID approvals are also urbanizing more rapidly before the introduction of the policy. Panel B then presents the time trends of budgetary revenue in the treated and the control districts after the propensity score matching. It shows a similar trend in budgetary revenue prior to the implementation of the TCID policy and a significant increase in budgetary revenue of the treated districts after 2010. Panels A and B in Figure 15 together suggest that the propensity score matching can mitigate potential selection bias by selecting a sample of comparable cites with parallel pre-treatment trends. In addition, Figure 16 shows that the treated and the control districts in the PSM sample tend to design similar FAR limits before 2010, and the treated districts start to design lower FAR limits after 2010. This is in line with the expectation that the TCID policy can increase local budgetary revenue in the central districts and thus reduce local FAR limits. I will formally test for the impact of the TCID policy on FAR design in section 4.

This paper also applies an event study approach to test for the parallel trend assumption for the PSM sample and to estimate the dynamic impacts of the TCID policy. Panel A of Figure 17 shows the impact of the TCID adjustment on the standardized budgetary revenue using the PSM sample. The estimated coefficients are insignificant before the implementation of the policy and become significant and positive after the administrative adjustment. This is in line with the expectation that the policy will break local administrative barriers and lead to infrastructure improvement and an increase in budgetary revenue. In addition, Panel B of Figure 17 shows the impact of the TCID policy on FAR limits using the PSM sample. Consistent with Figure 16, Panel B of Figure 17 shows insignificant estimated coefficients before the implementation of the TCID policy, and significant and negative coefficients after the adjustment.

This paper then re-estimates the impact of budgetary revenue on FAR design using the PSM sample and the corresponding results are reported in Table 4. All the IV estimates in columns (1) to (3) are statistically significant and have the expected signs. The F statistics suggest that weak instrument is not a concern, and the first-stage results reported in Table 4 show that the instrumental variable significantly correlates with budgetary revenue in an expected way. The more rigorous estimate in column (3) of Panel B suggests that a one standard deviation increase in local budgetary revenue will decrease FAR limit by 0.62, which is around 44% of the standard deviation of FAR limit in the baseline sample.

This paper concludes from these findings that the impact of budgetary revenue on FAR limit is well identified. In line with the main proposition from the theoretical framework, I find that local budgetary revenue has a negative impact on FAR design. As the theoretical framework implies, local governments trade-off between the benefits (fiscal revenue and housing supply) and the costs (negative externalities) of FAR design. If a local government can collect sufficient budgetary revenue from sources other than land sales, it will put more weight on the negative externalities caused by density and set lower FAR limits. Conversely, local governments with fewer budgetary revenue are more relied on land sales and will design higher FAR limits to raise more fiscal revenue.

3.4. Quantitative Analysis

To quantify the impact of land finance model on land use regulation design, this paper follows the prediction from the theoretical framework and conducts a quantitative analysis. As the theoretical framework suggests, if the land finance model was abolished and local public goods were funded by budgetary revenue only, the impact of local budgetary revenue on FAR limits would be insignificant.

In this section, I first predict local FAR limits by re-estimating a specification similar to equation (1) but at the county level. I aggregate all the plot level observations into a county level panel, and then re-estimate the impact of local budgetary revenue on FAR design. Table 5 presents the OLS and IV estimates at the county level. The estimates for budgetary revenue on FAR limits are robust and consistent with the plot level findings. Kleibergen-Papp F-statistics do not reveal a problem with weak identification. I base the counterfactual analysis on the TSLS specification reported in column (3) of Table 5. The specification yields a prediction of FAR limit conditional on local budgetary revenue, different land plot and city characteristics, as well as county and year fixed effects.

I then obtain a counterfactual scenario by predicting local FAR limits with the impact of budgetary revenue set to zero. As predicted in the theoretical framework, if the land finance model was abolished, local budgetary revenue would have no impact on FAR design. This exercise thus allows me to understand the quantitative importance of the Chinese land finance model on FAR design.

Table 6 reports the predicted FAR limits under the main scenario and the counterfactual scenario. It suggests that if the land finance model is abolished from the local fiscal system, the average FAR limit in China will increase slightly from 2.66 to 2.7. However, the impact of abolishing land finance model on FAR design is heterogeneous across different cities. For rich and economically developed cities such as Beijing, Shanghai, Suzhou, and Guangzhou, if local governments don’t finance public goods through land sales anymore, the average FAR limits will increase significantly by between 18.3% and 55.8%. As Figure B1 suggests, these rich cities are also faced with severe housing affordability issues, so relaxing the FAR restrictions could contribute to increasing housing supply and reducing housing prices. On the contrary, Cities such as Baoji, Linfen, Xining, and Lanzhou are less economically developed and have lower budgetary revenue compared with the above superstar cities. If the land finance model is abolished, FAR limits in these cities will decrease, which will reduce housing supply and the negative externalities caused by high construction densities. Figure 18 visualizes the counterfactual FAR limits across Chinese cities under the scenario when the land finance model is abolished. The comparison between Figure 18 and the actual FAR limits in Chinese cities suggests that the land finance model contributes the spatial difference in land use regulation design and housing affordability issues in China.

4. Additional Results and Robustness Check

4.1. The Impact of TCID Policy on FAR Design

In this sub-section, I directly estimate the impact of the TCID policy on FAR design. Figure 16 first presents both the annual and the quarterly average FAR limits in the treated and the control districts respectively using the PSM sample. Both panels in Figure 16 suggest a near-identical FAR trend prior to the administrative adjustment and a significant lower FAR limit in the treated districts after TCID policy. I then explore the quantitative impact of TCID policy on FAR design by estimating a difference-in-difference specification as shown below:

$$FAR_{icdgym} = \phi_d + \rho_g + \beta Post_y \times Treat_d + \delta_{ym} + \gamma' X_i + \tau' Z_{cy} + \varepsilon_{icdgym} \quad (3)$$

where $Post_y$ is a dummy equalling to zero if year y is prior to the administrative adjustment, and $Treat_d$ is a dummy equalling to one if county d is a pre-existing municipal district and within a prefecture that implements the TCID adjustment. The parameter of interest is β, measuring the impact of the administrative adjustment policy on FAR design.

Table A1 reports the estimation results using both the baseline sample and the PSM sample. In line with the main findings, columns (1) to (6) all report negative and statistically significant coefficients, suggesting that after the implementation of the TCID policy, the pre-existing municipal districts will design lower FAR limits compared with other districts and counties. The more credible estimate in column (6) suggests that the TCID policy decreases local FAR limits by 0.13.

4.2. Population Density and Negative Externality

To test for the assumption in the theoretical framework that high density causes negative externalities, I estimate the following equation using city-level panel data:

$$Ln(Y)_{cy} = \phi_c + \beta Ln(Density)_{cy} + \delta_t + \tau' Z_{cy} + \varepsilon_{cy} \quad (4)$$

where c indexes each city and y indexes time periods. The variable $Ln(Density)_{cy}$ represents the natural logarithm of population density of city c in year y. A vector of city fixed effects is represented by ϕ_c. δ_y is a set of time dummies (year fixed effects) and Z_{cy} is a set of city-level controls such as GDP per capita, average salary, and industry composition. The dependent variable $Ln(Y)_{cy}$ represents two different measures of air quality including PM10 and Air Quality Index (AQI). The parameter of interest is β, measuring the impact of population density on air quality.

The estimated results are reported in Table A2. All the estimated coefficients are positive and statistically significant, meaning that cities with higher population density have worse air quality. This is in line with the assumption in the theoretical framework that high density is associate with negative externalities.

4.3. FAR limits for Non-Residential Use

Does local budgetary revenue also influence the FAR design for non-residential use? To answer this question, I first compute the weighted average FAR limits for non-residential use across the country. As Figure B2 shows, there is no clear spatial pattern of the FAR design for industrial and commercial uses. I then re-estimate equation (1) using a sample of non-residential land plots and the results are reported in Table A3. The estimated impact of budgetary revenue on FAR limits for commercial and industrial uses are all insignificant.

These estimation results first mitigate the endogeneity concern of unobserved spatial characteristics in the main specification. One might argue that there are fewer land plots available in the more economically developed cities, and the scarcity of land plots might have substitutional impact on FAR limits, as local governments will design high FAR limits given the limitation of horizontal expansion. However, if these cities are indeed concerned about the availability of land plots and opt to design high FAR limits, they should also design high FAR limits for non-residential land parcels. As Table A3 shows, the estimated impact of local budgetary revenue on FAR limits for non-residential use is insignificant, suggesting that the main result is not driven by the geographical scarcity in more economically developed cities.

Table A3 also provides supportive evidence for this paper's theoretical framework. The negative effect of budgetary revenue on FAR design for residential use is driven by the mechanism that high FAR limit can increase residential land value and influence the substitution between land sales and local budgetary revenue. If FAR limit doesn't have a strong and positive impact on land value, then the impact of local budgetary revenue on FAR design will also be marginal. Table A4 reports the elasticity of land price per square meter with respect to FAR limit for different land uses. Columns (1) to (3) suggest that while this elasticity is around 43% for residential lands, it becomes much lower for other land uses. Especially for industrial use, the elasticity is still positive but only at around 7%. The marginal elasticity is reasonable as the FAR design for industrial use is mainly determined by the technical requirements of manufacturing companies. In this case, the quantity of properties to be built out upon an industrial land plot is not a major consideration for land bidders. Besides, some local governments in China intentionally lower the land price for commercial and industrial use to attract firms and manufacturing companies, which further weakens the fiscal motive of high FAR limit.

4.4. Transfer Payment from The Central Government

Another major source of fiscal revenue for local governments in China is the transfer payment from the central government. In this sub-section, I estimate the impact of central government transfer payment on FAR design. The prefecture-level fiscal transfer data comes from China Financial Statistics of Cities and Counties. Since the local public transfer data becomes unavailable after 2009, this paper uses the share of local government's transfer payment in 2007 and the annual national transfer payment trend to estimate yearly transfer payments at the local level. As equation (5) illustrates, $Transfer_{cy}$ represents the estimated transfer payment in prefecture-level city c in year y. $\frac{Transfer_{c2007}}{Total_{2007}}$ represents the share of city c's transfer payment relative to the national level in year 2007, and $Total_y$ denotes the national trend of transfer payment.

$$Transfer_{cy} = \frac{Transfer_{c2007}}{Total_{2007}} \times Total_y \tag{5}$$

This paper then studies the impact of the estimated local transfer payment on FAR limit by estimating a specification similar to equation (1). The results are reported in Table A5. All estimates are negative and statistically significant at 1% level. The most credible estimate in column (3) suggests that a one standard deviation increase in transfer payment will decrease FAR limits by 0.09. This finding is in line with proposition (1) that if local governments can collect sufficient fiscal revenue from sources other than land sales, they will design relatively low FAR limits to reduce the negative externalities caused by density. The estimated effect of transfer payment on FAR design is larger than the OLS estimation of budgetary revenue as reported in Table 2, potentially because transfer payment comes from the central government and is less influenced by local features compared with budgetary revenue. The endogeneity issues as discussed in section 3.2.1 are thus less pronounced in this specification.

4.5. Spatial Boundary Design

In this sub-section, I exploit the administrative boundaries to test for the robustness of the main results. One might argue that even the PSM sample from the main analysis is selected based on the observed local characteristics, and there is still a concern of unobserved local features. To mitigate this concern, I apply a spatial boundary design and select land parcels that are geographically close to each other. For instance, Figure B3 presents the land plots within 5 km away from the county boundary within a prefecture, Fuzhou. These land parcels tend to have near-identical neighbourhood and unobserved spatial features and are thus highly comparable. As shown in Figure B4, I select all the land parcels within 5 km away from county boundaries across the country and use these land transactions to perform empirical analysis. The estimation results are reported in Table A6. All the estimated coefficients from columns (1) to (3) are statistically significant and negative, suggesting that the main results are robust after I take into account unobserved local characteristics that might influence both local budgetary revenue and FAR design.

4.6. Placebo Test

Next, I mitigate the concern that the influence of the TCID policy on FAR design is spuriously documented outside the treatment periods, meaning that the estimated impact might be driven by the pre-existing and unobserved local trends during the process of urbanization, and these pre-trends might not be fully controlled for even after I conduct the propensity score matching. To mitigate the concern of the spurious treatment effect, I generate 1,000 random placebo treatment dates which are 1 to 3 years prior to the real treatment date. For instance, if a city implements the administrative adjustment in 2012, the randomly generated date will be between 2009 and 2011. I then estimate a specification similar to equation (3) using the randomly generated treatment date and the PSM sample. The cumulative probability and the kernel density of the estimated effect from 1,000 different placebo regressions are plotted in Figure B5. The vertical line represents the estimated impact of the TCID policy on FAR design from column (6) of Table A1. Only 16 estimates from these 1,000 placebo regressions are more negative than the estimated treatment effect, increasing the confidence that earlier findings are not spuriously driven by the pre-existing local trends during the urbanization process.

4.7. Prefecture-Level Budgetary Revenue

This paper then uses the prefecture-level budgetary revenue measure and re-estimates a specification similar to equation (1) to test for the robustness of the main findings. The results are reported in Table A7. All the estimated coefficients are still negative and statistically significant, suggesting that the impact of local budgetary revenue on FAR design is robust after I measure local fiscal capacity at a higher administrative level.

4.8. Drop Tier-1 cities and Municipalities

Four Tier-1 cities (Beijing, Shanghai, Guangzhou, and Shenzhen) and two municipalities (Tianjin and Chongqing) are reckoned as the most economically developed cities in China. To avoid potential bias caused by the unobserved features in these six superstar cities, this paper conducts a robustness check by estimating a sample excluding land transactions in these cities. The results are reported in Table A8. In line with the baseline findings, the estimated coefficients are all negative and statistically significant at 1% level, suggesting that the main results are robust after I mitigate potential bias introduced by superstar cities.

4.9. Before the Boom of Local Government Debt

Lastly, this paper conducts a robustness check to address the concern of local government debt. After the 2008 financial crisis, the central government in China launched a fiscal stimulus program named the 'four trillion stimulus package' to boost economy. Followed by this stimulus program, local governments in China have increasingly issued debts to finance infrastructure investments, and most of these debts are guaranteed by future land sale revenue. Due to the fiscal pressure of repaying local debts, governments might set relatively high FAR limits to acquire more land sale revenue. As shown in Figure B6, the large-scale issue of local government debts started in 2014. This paper thus estimates a subsample of land transactions between 2005 and 2013 to test for the robustness of the main findings. During this period, local government debt is not likely to have a major impact on FAR design. Table A9 reports the results and shows that all estimates are negative and statistically significant. In line with the baseline estimation, Table A9 suggests that budgetary revenue has a negative effect on FAR design before the boom of local government debt in China.

5. Conclusion

This paper explores the determinants of FAR limits in China by first proposing a spatial equilibrium framework and showing that local governments trade-off between the benefits and the costs of high construction density when designing FAR limits. Cities with sufficient budgetary revenue opt to set relatively low FAR limits to reduce negative externalities and attract more population. Exploiting a comprehensive dataset of land transactions and a PSM-IV strategy, I find that a one standard deviation increase in local budgetary revenue decreases FAR limits by 0.6. I then base a counterfactual analysis on the IV specification and finds that the land finance model has a quantitatively meaningful impact on FAR design in China, especially in super star cities.

The land finance model and land use regulation design have important implications for the Chinese economy. On one hand, Tier-1 cities and cities along the southeast coast have sufficient local budgetary revenue and design relatively low FAR limits, which reduce housing supply and push up housing prices. As Figure B1 shows, cities along the southeast coast have higher housing prices and face more severe housing affordability problems compared with other cities in the country. Restrictive land use regulations could also lead to the wealth inequality between homeowners and young first-time buyers within these cities. On the other hand, some local governments in the less developed western and middle regions cannot collect sufficient budgetary revenue from local taxes and choose to design higher FAR limits to acquire more land sale revenue. These cities are not experiencing economic prosperity as Beijing and Shanghai and thus cannot attract superstar firms and high-skilled labours. As a result, many high-rise buildings in these cities are constructed and then left vacant. Despite the staggeringly high housing prices in Tier-1 cities, properties in some lower-Tier cities are sold for only 300 RMB/m^2, which is around 33 GBP/m^2 (Xinhuanet, 2019).[16] The regional inequality between

[16] Based on the currency exchange rate in September 2021.

the ‘under-occupied cities’ and the ‘unaffordable cites’ is largely driven by the fact that land sale serves as a major source of fiscal revenue for many local governments. While this paper studies the determinants of FAR design, future research can explore how Chinese cities can improve the current ‘Land Finance Model’ and develop in a sustainable way.

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Tables

Table 1:
Descriptive Statistics

	Observations	Mean	SD	Max	Min
Panel A: Land parcel characteristics					
FAR upper limit	202816	2.8	1.4	8	1
Transaction price (10,000 RMB)	202816	5300	19977.1	1020000	0.0001
Distance to CBD (km)	202816	42.2	27.6	100	0.0001
Land area (10,000 m^2)	202816	2.5	94.7	42559	0.00004
Auction type 1 (zhao)	202816	0.01	0.1	1	0
Auction type 2 (pai)	202816	0.2	0.4	1	0
Auction type 3 (gua)	202816	0.5	0.5	1	0
Auction type 4 (negotiation)	202816	0.3	0.4	1	0
Auction type 5 (huabo)	202816	0.01	0.1	1	0
Land quality	202816	4.6	4.4	18	0
Panel B: Prefectural-level characteristics					
Budgetary revenue (1 million RMB)	3027	17425.8	41324.6	664226.4	208.2
Population (1 million)	3027	4.5	3.1	33.9	0.2
% Employment in the agricultural sector	3027	2.9	6.6	74	0
% Employment in the tertiary sector	3027	52.5	12.9	94.8	9.9
Average salary (RMB)	3027	40338.3	17578.9	320626.3	4958
Number of universities	3027	8.5	14.4	92	1
Number of hospitals	3027	212.5	188	3052	5
Panel C: County-level characteristics					
Budgetary revenue (1 million RMB)	15380	1312.6	2613.6	67298.4	11.2
TCID policy treatment dummy	1823	0.1	0.3	1	0

Table 2:
The Effect of Budgetary Revenue on FAR

Panel A: OLS results			
Specifications	(1)	(2)	(3)
Budgetary revenue	-0.0756***	-0.0834***	-0.0772***
	(0.0120)	(0.0137)	(0.0136)
R^2	0.4024	0.5336	0.5340
Panel B: IV results			
Budgetary revenue	-0.4296***	-0.5248***	-0.6013***
	(0.0909)	(0.1228)	(0.1601)
Kleibergen-Paap rk Wald F-statistic	90.08	67.24	39.77
Panel C: first-stage results			
TCID × Post	0.4968***	0.4066***	0.3197***
	(0.0523)	(0.0496)	(0.0507)
R^2	0.9040	0.9347	0.9369
N	202797	195070	195070
Land parcel controls [1)]	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Grid FEs	No	Yes	Yes
City controls [2)]	No	No	Yes

Notes: [1)] Land parcel controls include land area, distance to CBD, type of auction, land quality, longitude and latitude of the land parcel. [2)] City controls include population, average salary, local industry composition, number of universities and number of hospitals. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table 3:
Propensity Score Matching Results

	Before Matching			After Matching		
Variables	Treated cities	Control cities	P value	Treated cities	Control cities	P value
Variables used in PSM						
Population (10,000)	150	107	0.001	150	160	0.72
Pop. growth rate (%)	3.2	1.7	0.18	3.2	4	0.72
Budgetary revenue (1 million RMB)	9374	4220	0	9374	7754	0.53
GDP per capita (RMB)	51710	41307	0.01	51710	46625	0.45
% Employment (secondary industry)	46.4	45.7	0.74	46.4	45.4	0.69
% Employment (tertiary industry)	53	52.5	0.82	53	54	0.67
Variables not used in PSM						
Population density per km^2	463	399	0.13	463	568	0.16
Average salary (RMB)	32230	30417	0.04	32230	32194	0.98

Table 4:
The Effect of Budgetary Revenue on FAR (PSM Sample)

Panel A: OLS results			
Specifications	(1)	(2)	(3)
Budgetary revenue	-0.0142	-0.0418*	-0.0232
	(0.0229)	(0.0253)	(0.0260)
R^2	0.3279	0.4652	0.4663
Panel B: IV results			
Budgetary revenue	-0.4321**	-0.6085***	-0.6153***
	(0.2076)	(0.2264)	(0.2363)
Kleibergen-Paap rk Wald F-statistic	31.84	26.74	28.11
Panel C: first-stage results			
TCID × Post	0.2123***	0.2232***	0.2123***
	(0.0376)	(0.0432)	(0.0400)
R^2	0.8321	0.8701	0.8799
N	22016	21260	21260
Land parcel controls [1)]	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Grid FEs	No	Yes	Yes
City controls [2)]	No	No	Yes

Notes: [1)] Land parcel controls include land area, distance to CBD, type of auction, land quality, longitude and latitude of the land parcel. [2)] City controls include population, average salary, local industry composition, number of universities and number of hospitals. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table 5:
The Effect of Budgetary Revenue on FAR

Panel A: OLS results		
Specifications	(1)	(2)
Budgetary revenue	-0.0913***	-0.0800***
	(0.0146)	(0.0140)
R^2	0.5697	0.5708
Panel B: IV results		
Budgetary revenue	-0.2421***	-0.2214**
	(0.0778)	(0.0887)
Kleibergen-Paap rk Wald F-statistic	45.76	37.55
Panel C: first-stage results		
TCID × Post	0.7475***	0.6329***
	(0.1104)	(0.1033)
R^2	0.8908	0.8951
N	15345	15345
Land parcel controls [1]	Yes	Yes
Year FEs	Yes	Yes
County FEs	Yes	Yes
City controls [2]	No	Yes

Notes: [1] Land parcel controls include average land area, average distance to CBD, average longitude, and average latitude. [2] City controls include population, average salary, local industry composition, number of universities and number of hospitals. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table 6:
Quantitative Analysis

Variable	Average FAR	Predicted FAR	Predicted FAR without land finance model	%change in FAR
National mean value	2.85	2.66	2.7	1.5%
Beijing	2.28	2.34	3.42	46.2%
Shanghai	1.42	1.58	2.25	42.4%
Suzhou	1.95	1.9	2.96	55.8%
Guangzhou	3.53	3.56	4.21	18.3%
Baoji	3.02	2.76	2.69	-2.5%
Linfen	3.27	2.87	2.83	-1.4%
Xining	3.47	3.36	2.28	-32.1%
Lanzhou	2.98	3.37	3.34	-0.9%

Figures

Fig. 1:
Fiscal Revenue and Land Revenue in China

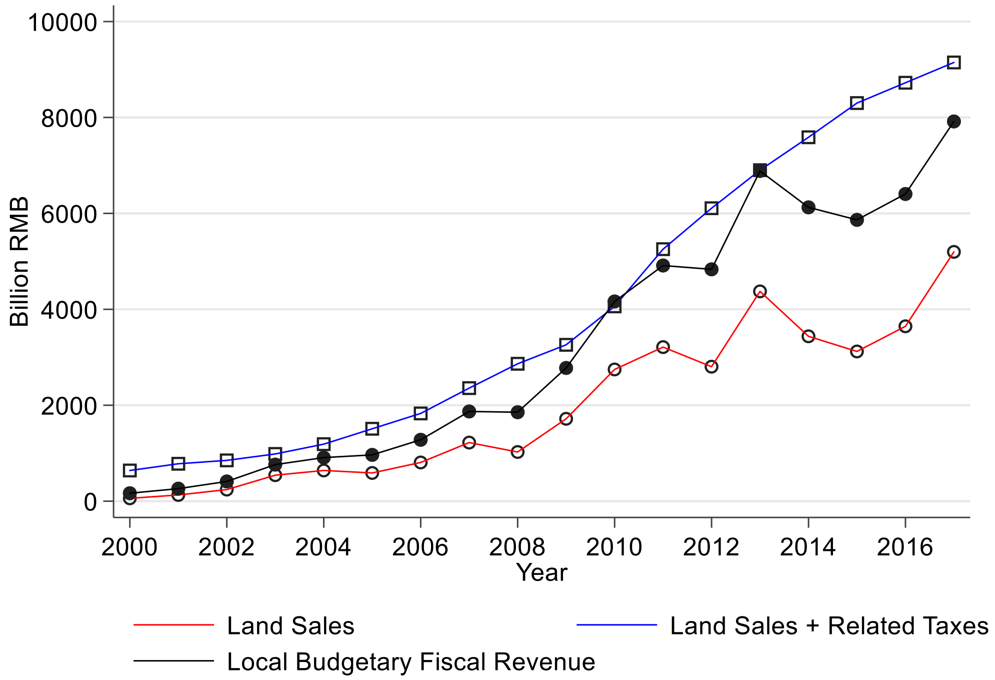


Fig. 2:
Land Price and FAR Limit (Linear Correlation)

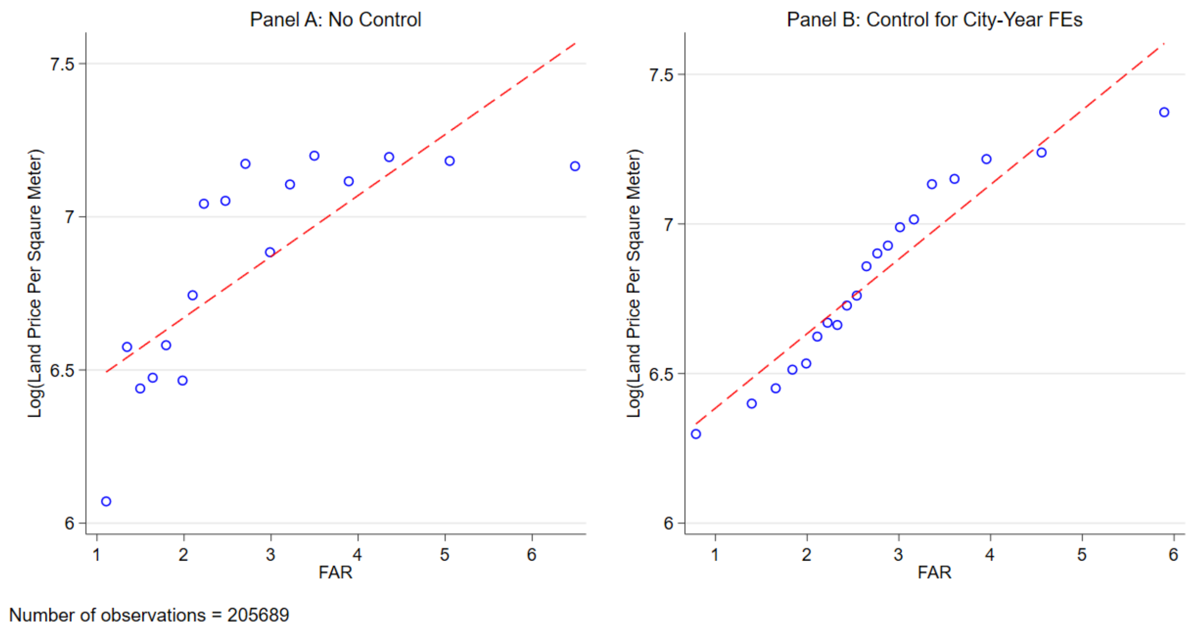
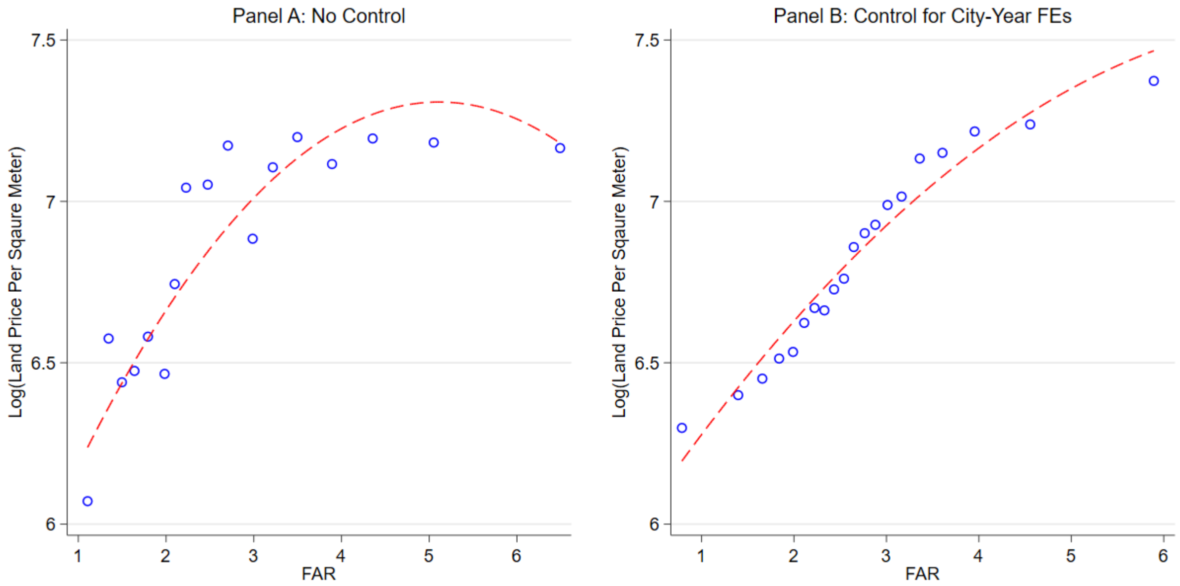
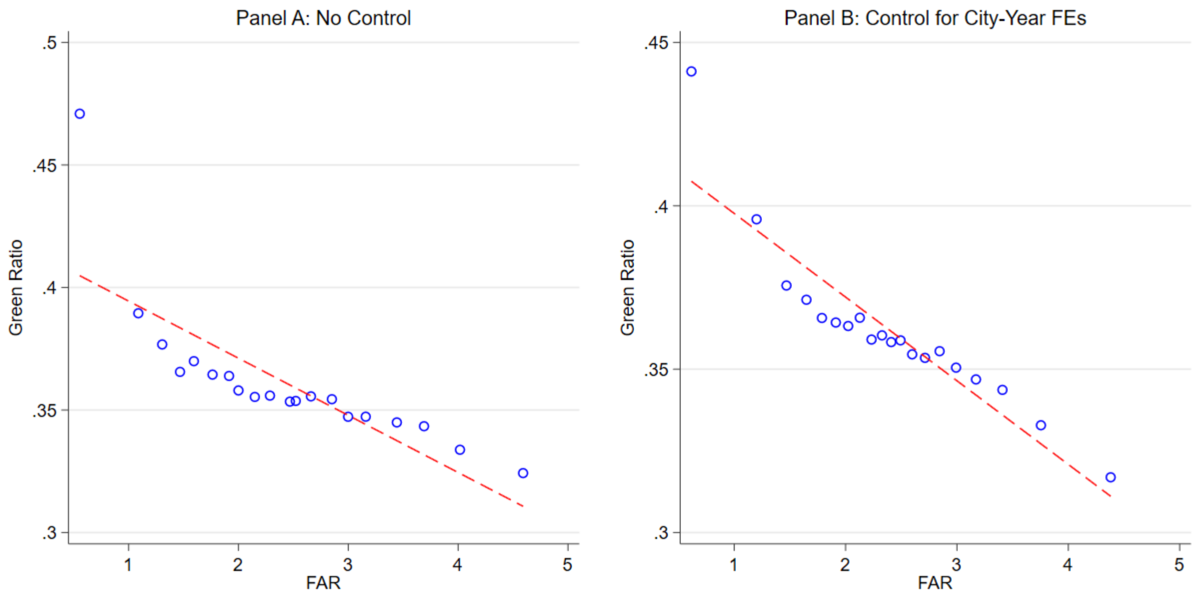


Fig. 3:
Land Price and FAR Limit (Quadratic Correlation)



Number of observations = 205689

Fig. 4:
Green Ratio and FAR Limit



Number of obs. = 39807

Fig. 5:
Prefectural-level Budgetary Revenue Per Person in 2017

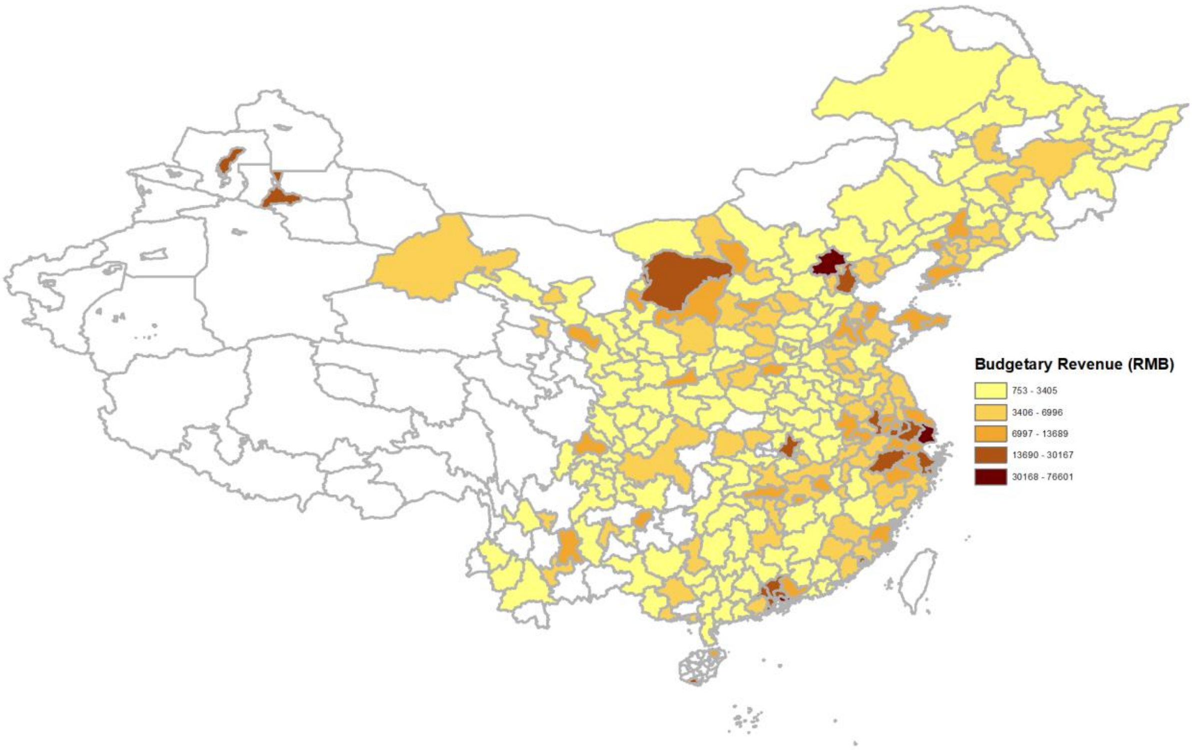


Fig. 6:
Weighted Average FAR for Residential Use

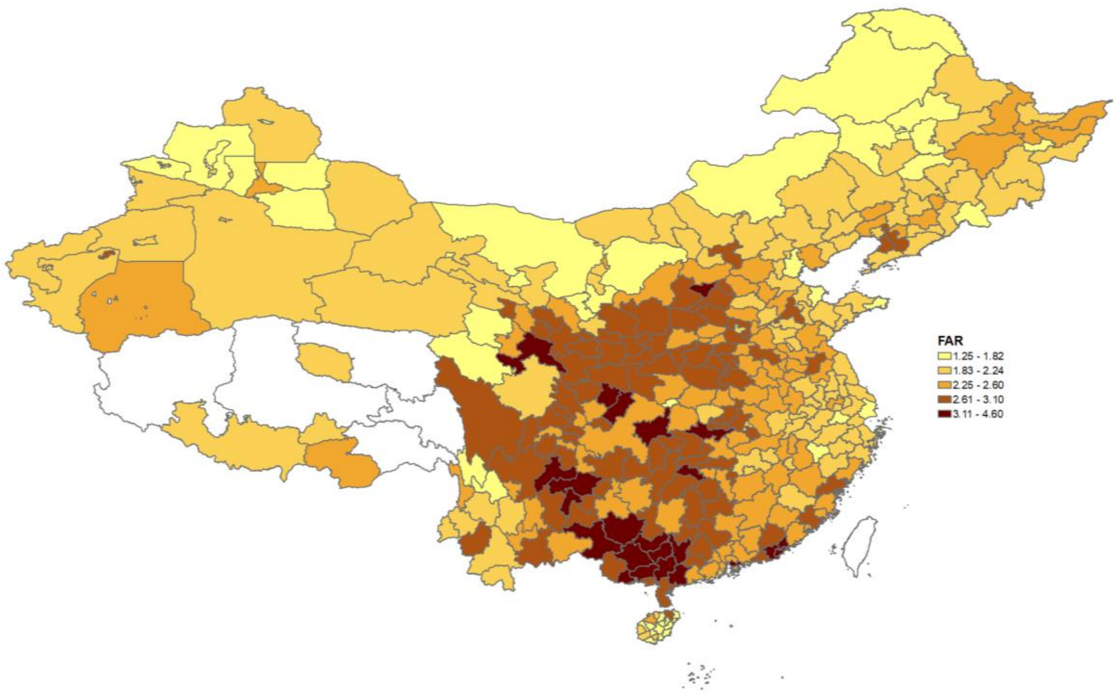


Fig. 7:
The Optional FAR Design (Main Case)

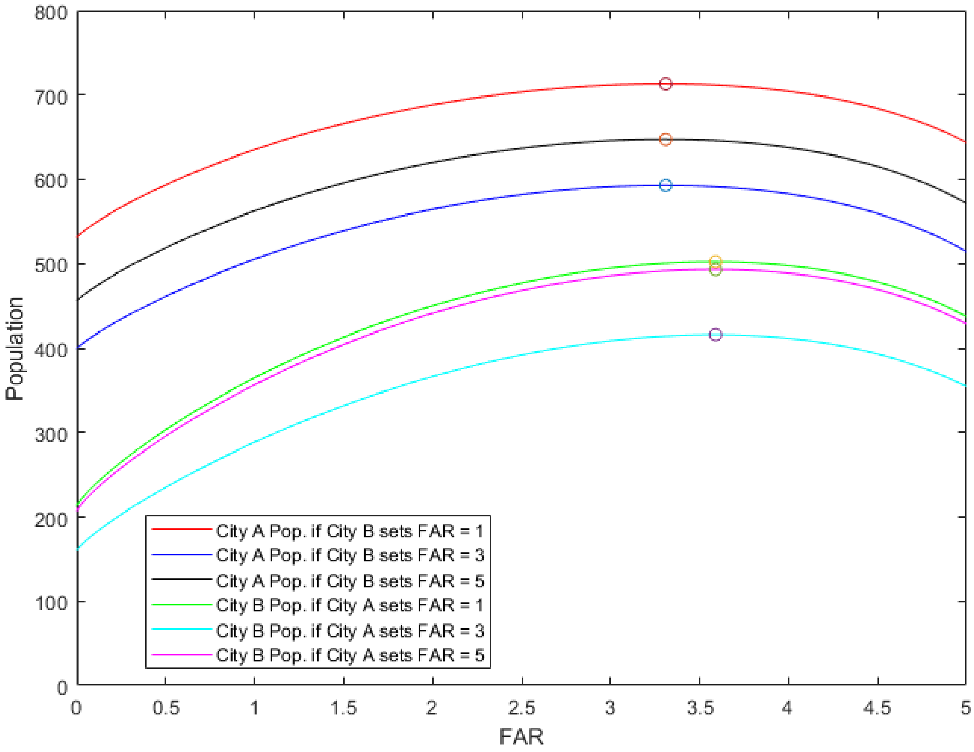


Fig. 8:
The Optional FAR Design (Land Finance Model Abolished)

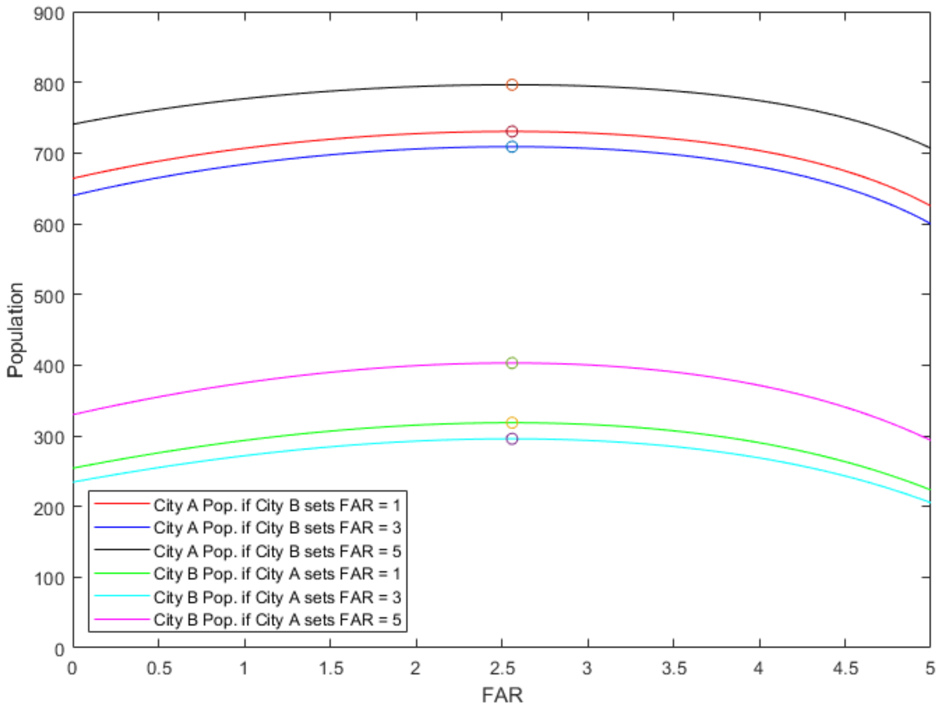


Fig. 9:
Geocoded Land Parcels

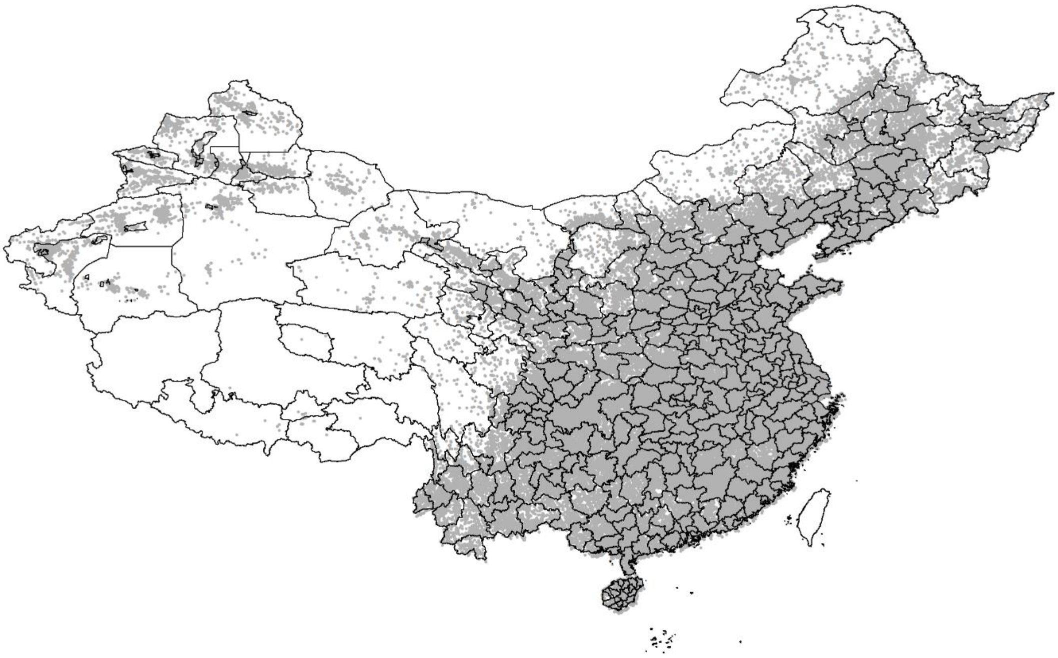


Fig. 10:
Land Parcels and 3km × 3km Grids in Beijing

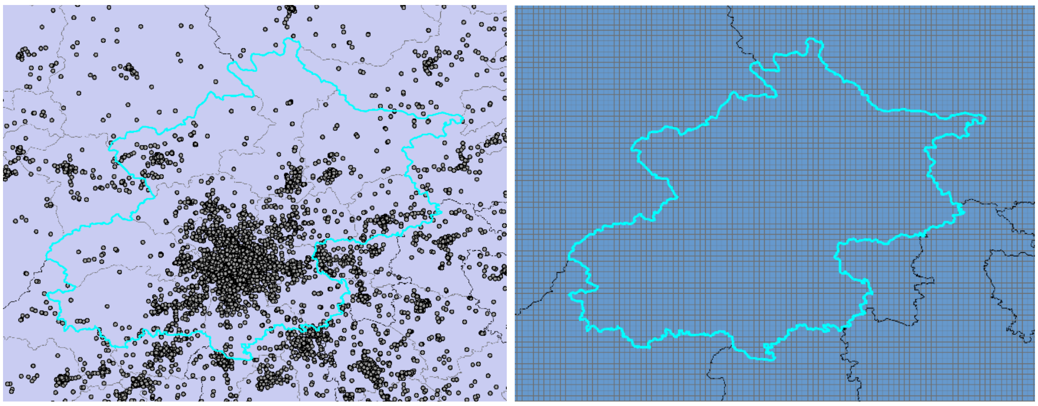


Fig. 11:
Local Administrative Division in China

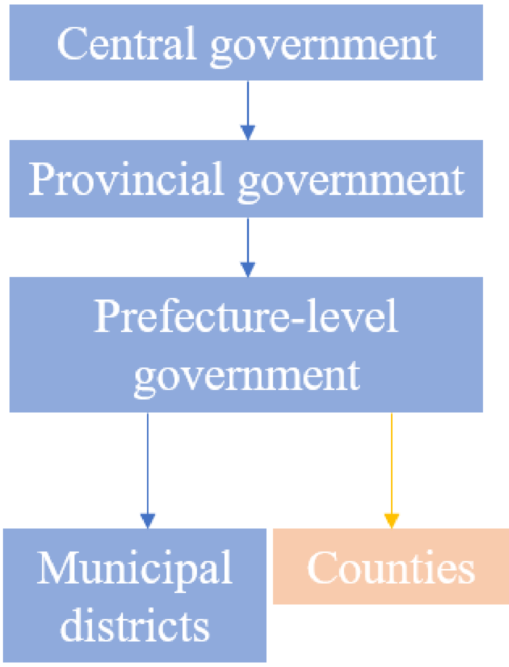


Fig. 12:
The Number of Administrative Adjustments

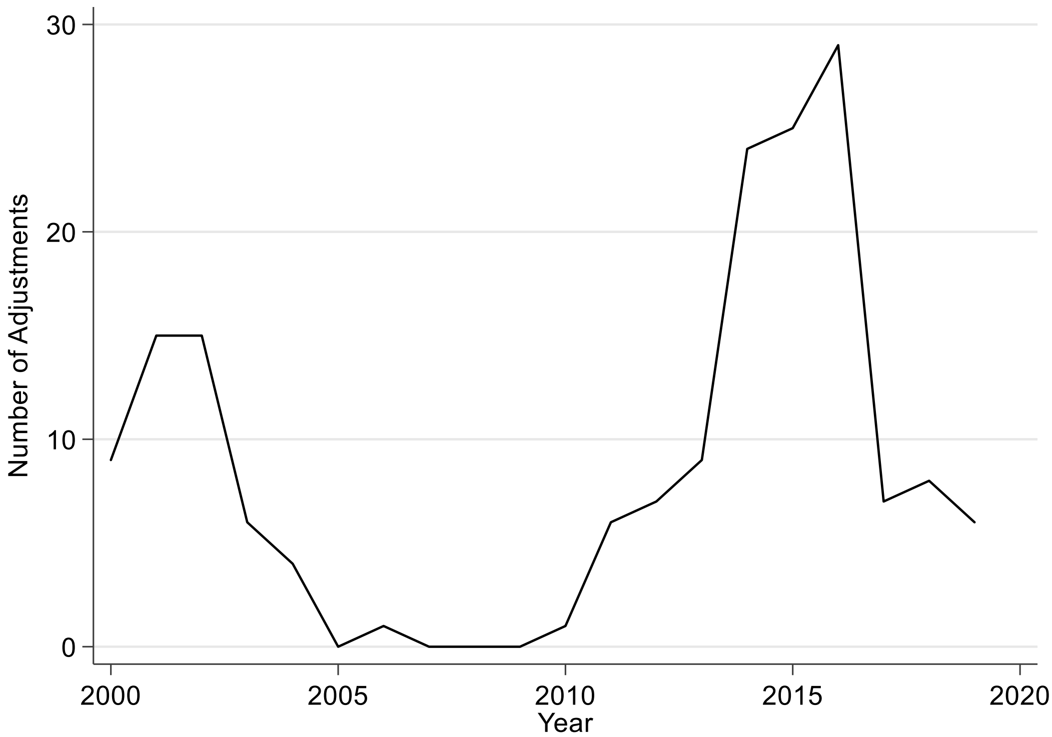


Fig. 13:
Cities with the TCID Policy in China

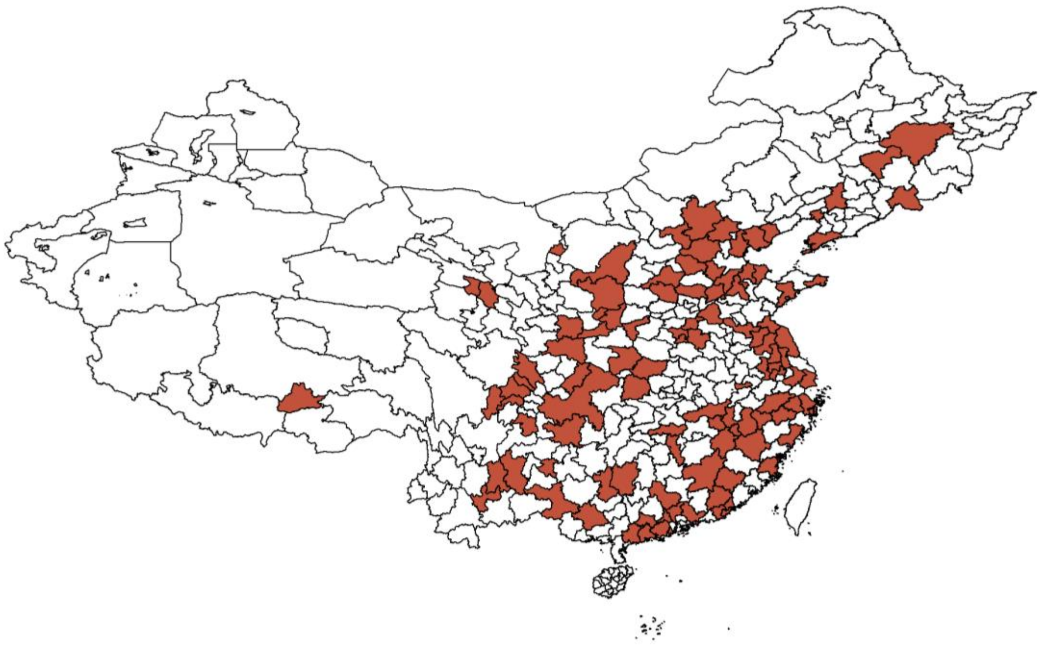


Fig. 14:
Turning County into District – Example of Xi'an

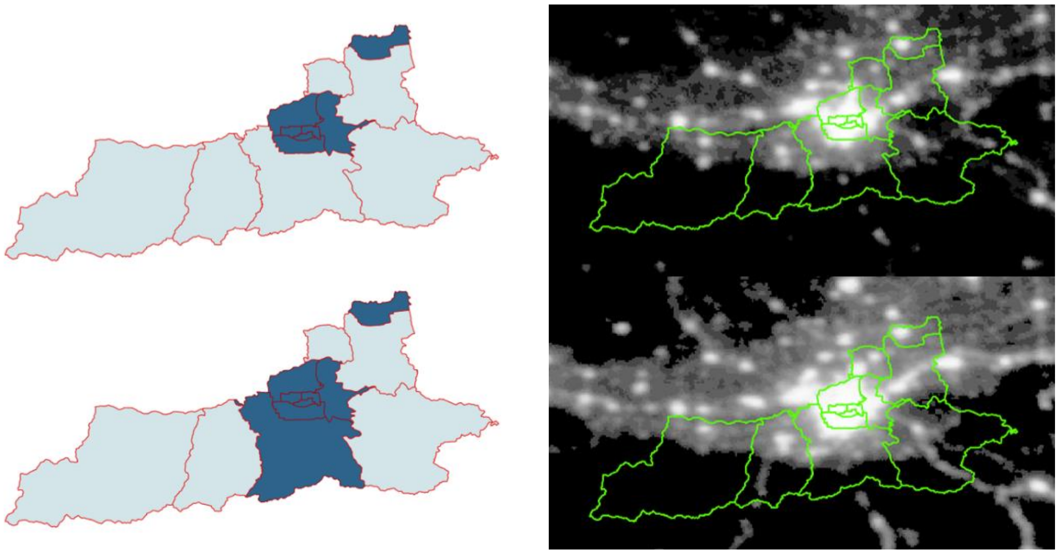


Fig. 15:
Average Budgetary Revenue (Before PSM)

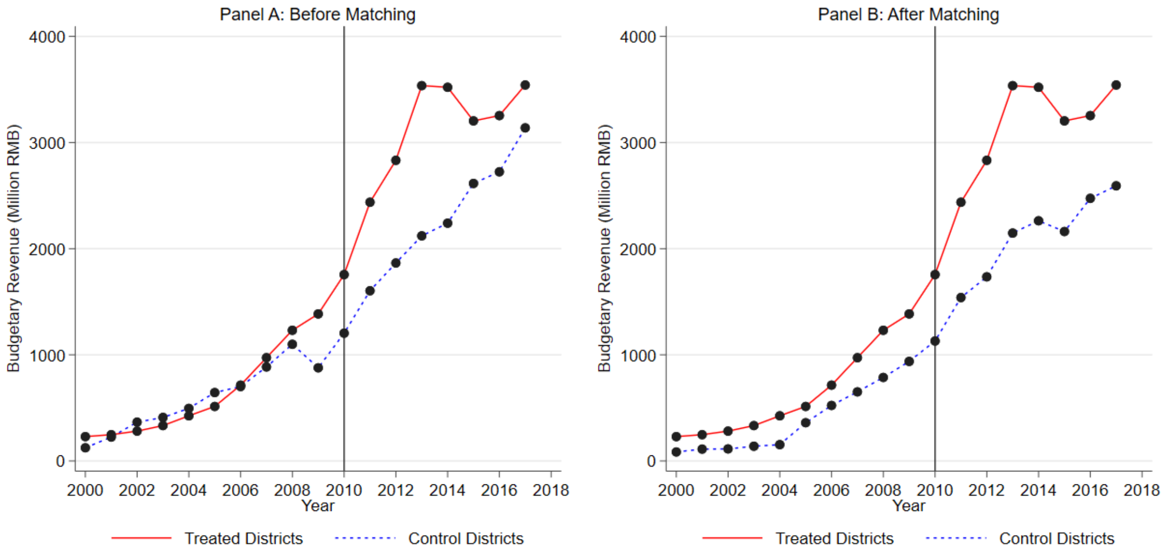


Fig. 16:
Annual Average FAR between 2007 and 2018 (PSM Sample)

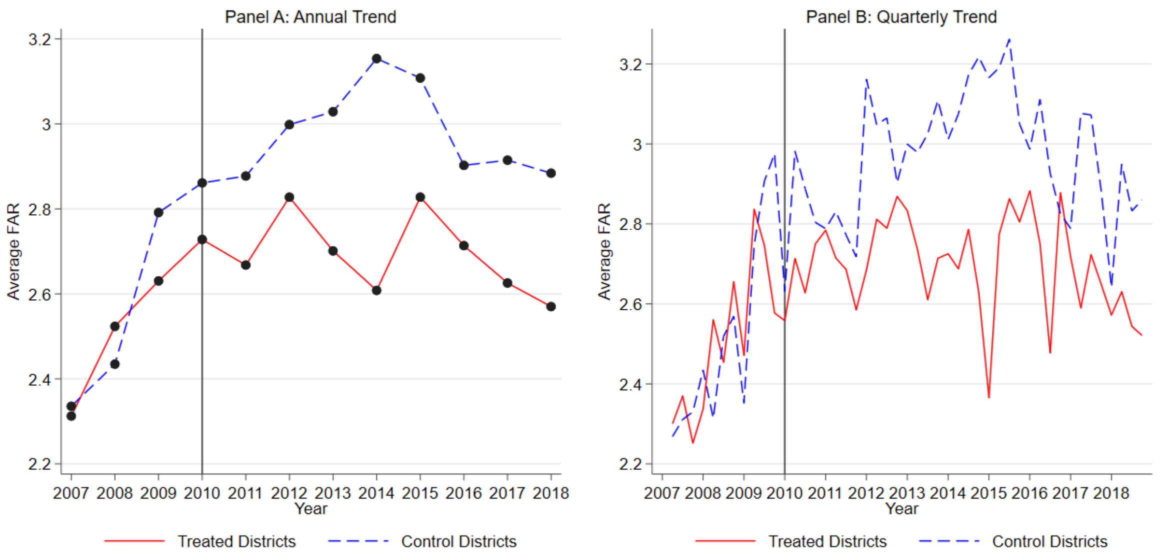


Fig. 17:
Event Study Analysis

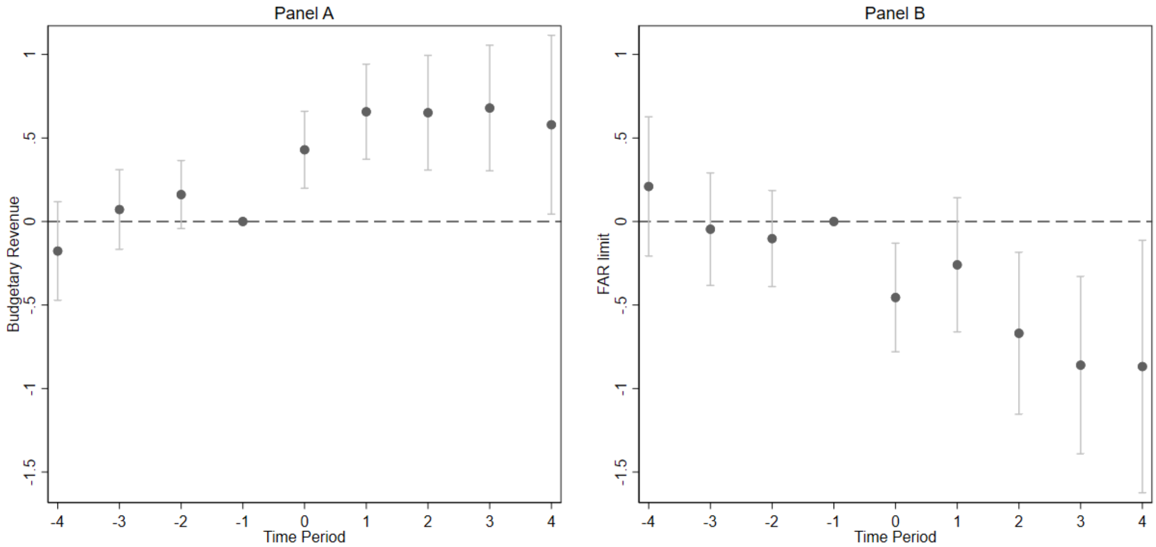
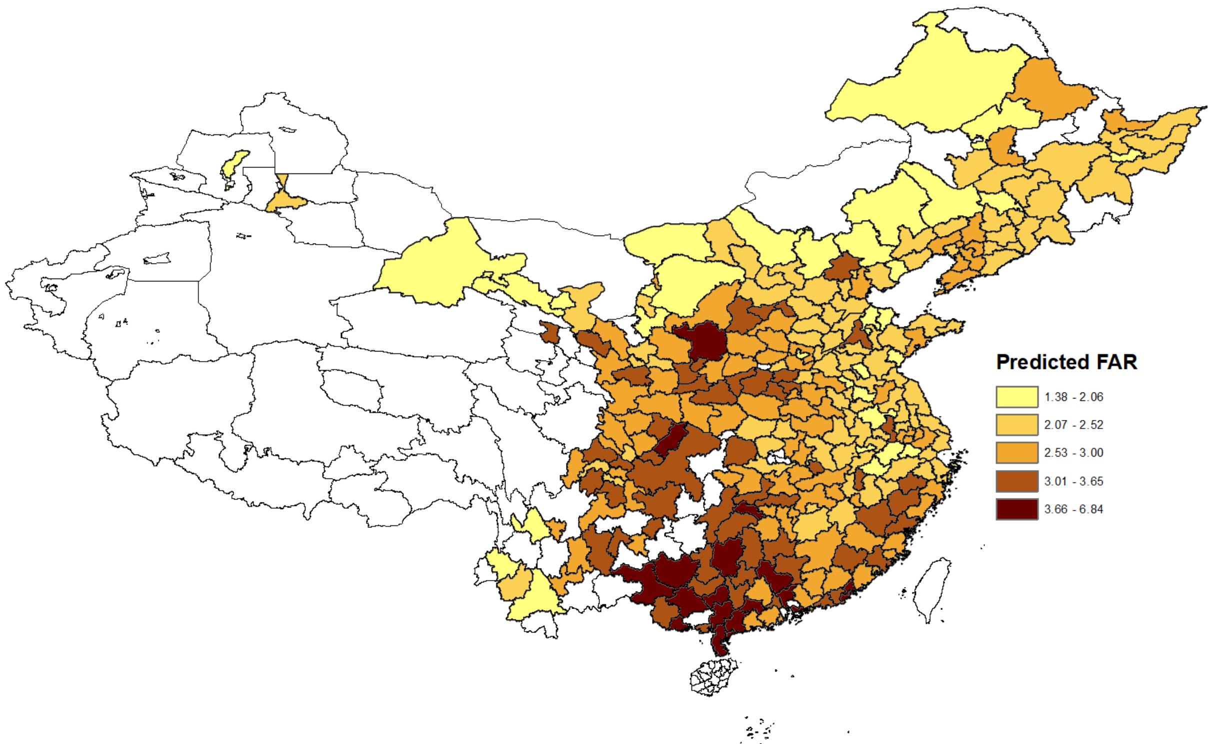


Fig. 18:
Quantitative Analysis



Appendices

Appendix A: Appendix Tables

Table A1:
The Effect of Administrative Adjustment on FAR

Specifications	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Sample	Baseline Sample			PSM Sample		
TCID × Post	-0.1855***	-0.1967***	-0.1733***	-0.0917**	-0.1358***	-0.1306***
	(0.0591)	(0.0639)	(0.0621)	(0.0431)	(0.0464)	(0.0458)
Land parcel controls [1)]	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Grid FEs	No	Yes	Yes	No	Yes	Yes
City controls [2)]	No	No	Yes	No	No	Yes
N	202797	195070	195070	22016	21260	21260
R^2	0.4022	0.5335	0.5339	0.3282	0.4655	0.4667

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A2:
Population Density and Negative Externality

Specifications	(1)	(2)	(3)	(4)
	Log(PM10)	Log(PM10)	Log(AQI)	Log(AQI)
Log(population density)	0.2372*	0.2413*	0.1836**	0.1848**
	(0.1331)	(0.1292)	(0.0917)	(0.0893)
Year FEs	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City Controls [1)]	No	Yes	No	Yes
N	821	821	821	821
R^2	0.8670	0.8716	0.7407	0.7476

Notes: [1)] City controls include average salary, the proportions of employment in the agricultural industry and the tertiary industry. Standard errors are clustered at the prefecture level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A3:
The Effect of Budgetary Revenue on FAR (Non-residential Uses)

Specifications	(1)	(2)	(3)	(4)
Dependent variable	FAR commercial OLS	FAR commercial IV	FAR industrial OLS	FAR industrial IV
Budgetary revenue	0.0053	-0.1532	0.0077	0.0235
	(0.0149)	(0.0997)	(0.0069)	(0.1100)
Land parcel controls [1)]	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
Grid FEs	Yes	Yes	Yes	Yes
City controls [2)]	Yes	Yes	Yes	Yes
N	84447	84447	124001	124001
R^2	0.4925		0.7110	
Kleibergen-Paap rk Wald F-statistic		40.3		18.59

Notes: [1)] City controls include average salary, GDP per capita, the proportions of employment in the agricultural and tertiary sectors. Standard errors are clustered at the prefecture level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A4:
The Elasticity of Land Price with Respect to FAR

Specifications	(1)	(3)	(4)
Dependent variable	Ln(land price) residential use	Ln(land price) commercial use	Ln(land price) industrial use
Ln(FAR)	0.4281***	0.2856***	0.0717***
	(0.0325)	(0.0094)	(0.0087)
Land parcel controls [1)]	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Grid FEs	Yes	Yes	Yes
City controls [2)]	Yes	Yes	Yes
N	195070	87645	135393
R^2	0.7125	0.6989	0.7791

Notes: [1)] See Table 2. [2)] City controls include all the city controls as indicated in Table 2 as well as local budgetary revenue. Standard errors are clustered at the grid level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A5:
The Effect of Transfer Payment on FAR

Specifications	(1) FAR	(2) FAR	(3) FAR
Transfer payment	-0.1502***	-0.1318***	-0.0919***
	(0.0260)	(0.0269)	(0.0288)
Land parcel controls [1)]	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
City FEs	Yes	Yes	Yes
Grid FEs	No	Yes	Yes
City controls [2)]	No	No	Yes
N	246143	236947	236947
R^2	0.2677	0.5250	0.5253

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. The transfer payment variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A6:
The Effect of Budgetary Revenue on FAR (Spatial Boundary Design)

Specifications	(1) OLS	(2) OLS	(3) OLS
Budgetary revenue	-0.0733*	-0.1029**	-0.1088**
	(0.0377)	(0.0469)	(0.0491)
Land parcel controls [1)]	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Grid FEs	No	Yes	Yes
City controls [2)]	No	No	Yes
N	18769	17772	17772
R^2	0.4592	0.5551	0.5565

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A7:
The Effect of Prefecture Level Budgetary Revenue on FAR

Specifications	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
Budgetary revenue	-0.1173***	-0.1182***	-0.1140***			
	(0.0139)	(0.0168)	(0.0173)			
Budgetary revenue per person				-0.0692***	-0.0602***	-0.0988***
				(0.0135)	(0.0144)	(0.0169)
Land parcel controls [1)]	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Grid FEs	No	Yes	Yes	No	Yes	Yes
City controls [2)]	No	No	Yes	No	No	Yes
N	202793	195064	195064	202793	195064	195064
R^2	0.4027	0.5337	0.5340	0.4022	0.5334	0.5340

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A8:
Robustness Check: Drop Tier-1 Cities and Municipalities

Specifications	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
Budgetary revenue	-0.0841***	-0.0918***	-0.0899***	-0.4270***	-0.5370***	-0.5691***
	(0.0151)	(0.0153)	(0.0155)	(0.1283)	(0.1526)	(0.1704)
Land parcel controls [1)]	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Grid FEs	No	Yes	Yes	No	Yes	Yes
City controls [2)]	No	No	Yes	No	No	Yes
N	200039	192559	192559	200039	192559	200039
R^2	0.4037	0.5339	0.5342			
Kleibergen-Paap rk Wald F-statistic				72.61	47.85	38.42

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A9:
Robustness Check (Sample before 2014)

Specifications	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	IV	IV	IV
Budgetary revenue	-0.0345**	-0.0400**	-0.0339*	-0.7294**	-0.8205**	-1.2887*
	(0.0165)	(0.0195)	(0.0191)	(0.2981)	(0.3208)	(0.6819)
Land parcel controls [1)]	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Grid FEs	No	Yes	Yes	No	Yes	Yes
City controls [2)]	No	No	Yes	No	No	Yes
Time period	2005-2013					
N	128078	121524	121524	128078	121524	121524
R^2	0.4443	0.5709	0.5715			
Kleibergen-Paap rk Wald F-statistic				33.95	22.52	7.08

Notes: [1)] See Table 2. [2)] See Table 2. Standard errors are clustered at the grid level. The budgetary revenue variable is standardized. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Appendix B: Appendix Figures

Fig. B1:
Housing Affordability in China in 2017

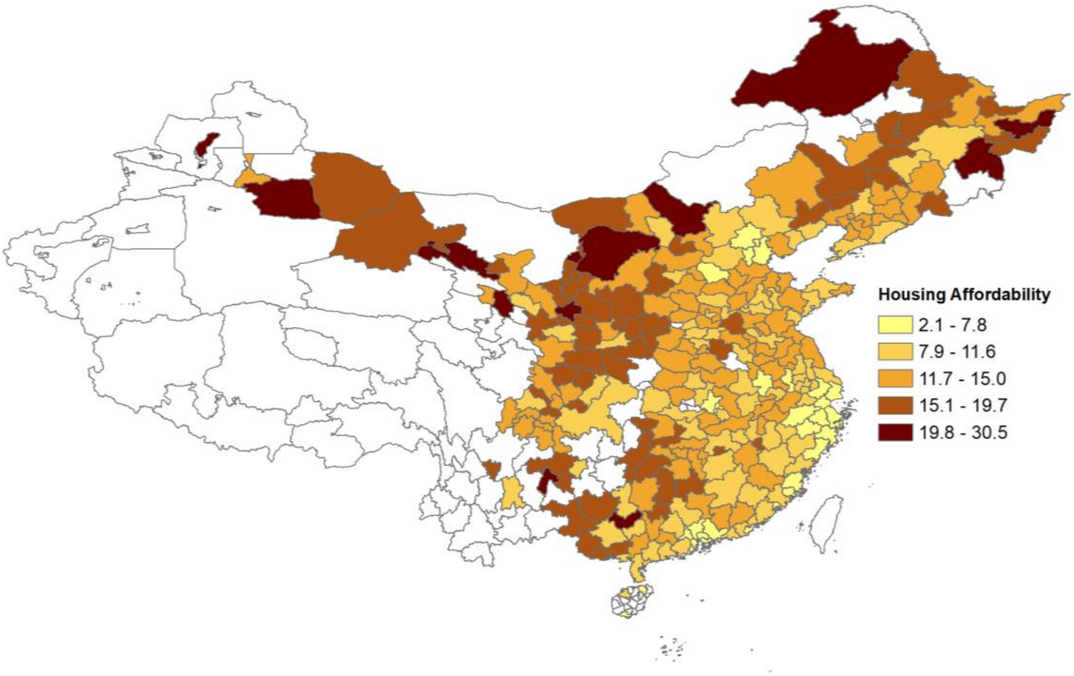


Fig. B2:
Weighted Average FAR for Commercial and Industrial Uses

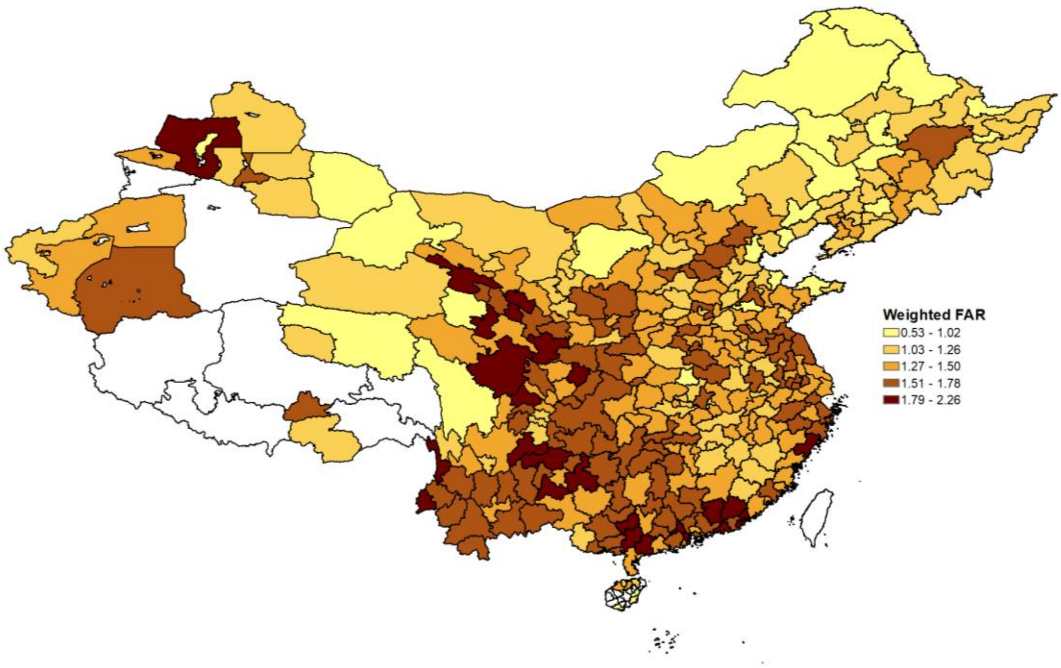


Fig. B3:
Land Plots Close to the County Boundary in Fuzhou (Jiangxi Province)

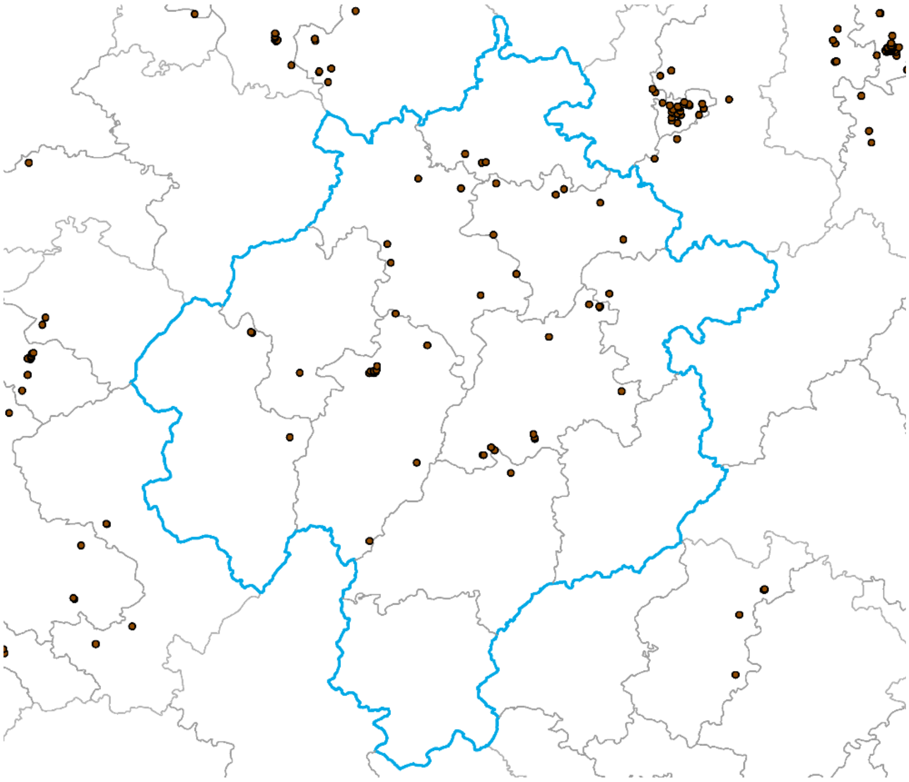


Fig. B4:
Land Plots Close to the County Boundary in China

Fig. B5:
Placebo Test

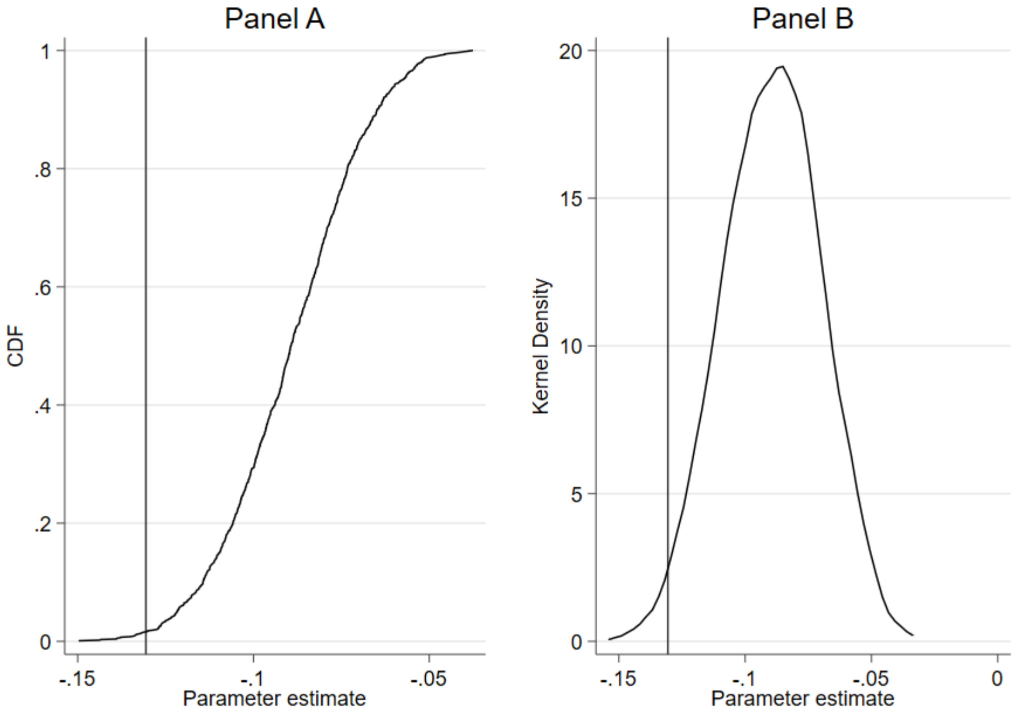
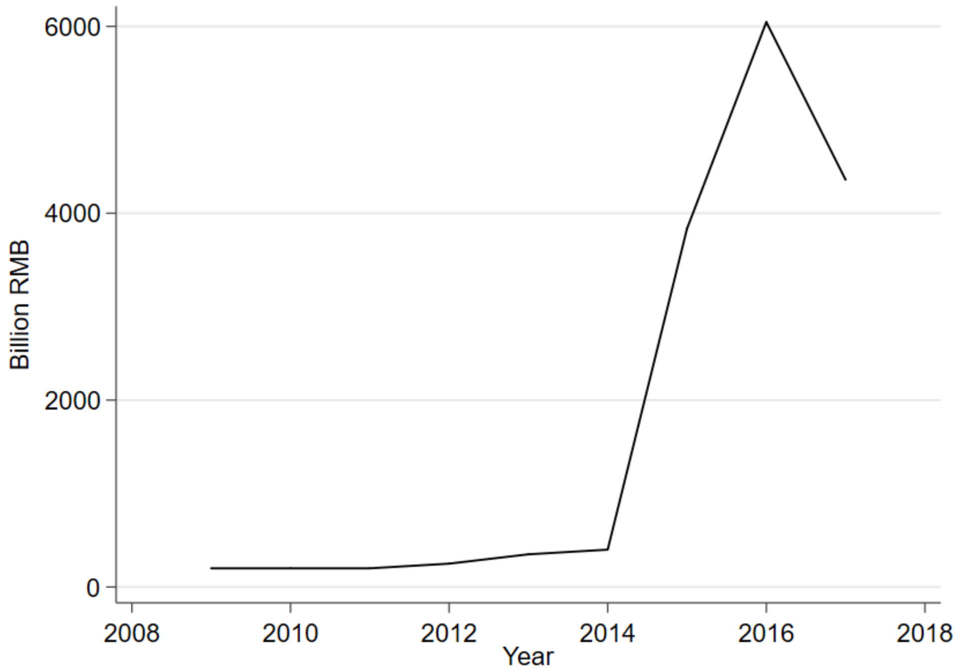


Fig. B6:
Local Government Debt in China



Note: Estimates from Suning Institute of Finance

Appendix C: Theoretical Appendix

To prove $\frac{\partial f^*}{\partial B} < 0$

The population of a city under the spatial equilibrium is given by:

$$L = \frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} (NSf + d)A(NSr + B)^{\beta}\theta}{\bar{U}}$$

Let ψ denote $\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}$. Local government design FAR f to maximize population. The first order condition is:

$$\frac{\partial L}{\partial f} = 0$$

$$\psi NSA(NSr + B)^{\beta}\theta + \psi(NSf + d)NSA\beta(NSr + B)^{\beta-1}\frac{\partial r}{\partial f}\theta + \psi(NSf + d)A(NSr + B)^{\beta}\frac{\partial \theta}{\partial f} = 0$$

$$\psi(NSf + d)NSA\beta(NSr + B)^{-1}\frac{\partial r}{\partial f}\theta = -\psi(NSf + d)A\frac{\partial \theta}{\partial f} - \psi NSA\theta$$

$$(NSr + B)^{-1} = \frac{-\psi(NSf + d)A\frac{\partial \theta}{\partial f} - \psi NSA\theta}{\psi(NSf + d)NSA\beta\frac{\partial r}{\partial f}\theta}$$

$$B = \frac{-\psi(NSf + d)NSA\beta\frac{\partial r}{\partial f}\theta}{\psi(NSf + d)A\frac{\partial \theta}{\partial f} + \psi NSA\theta} - NSr$$

The derivative of B with respect to the optimal FAR limit f^* is thus:

$$\frac{\partial B}{\partial f} = \frac{-\psi N^2S^2A\beta\frac{\partial r}{\partial f}\theta - \psi(NSf+d)NSA\beta\frac{\partial^2 r}{\partial^2 f}\theta - \frac{\partial \theta}{\partial f}\psi(NSf+d)NSA\beta\frac{\partial r}{\partial f}}{\psi(NSf+d)A\frac{\partial \theta}{\partial f} + \psi NSA\theta} +$$
$$\frac{\psi(NSf+d)NSA\beta\frac{\partial r}{\partial f}\theta\left(\psi NSA\frac{\partial \theta}{\partial f} + \psi(NSf+d)A\frac{\partial^2 \theta}{\partial^2 f} + \psi NSA\frac{\partial \theta}{\partial f}\right)}{\left(\psi(NSf+d)A\frac{\partial \theta}{\partial f} + \psi NSA\theta\right)^2} - NS\frac{\partial r}{\partial f}$$

Given the following inequalities:

$$\frac{\partial r}{\partial f} > 0, \frac{\partial^2 r}{\partial^2 f} < 0$$

$$\frac{\partial \theta}{\partial f} < 0, \frac{\partial^2 \theta}{\partial^2 f} < 0$$

$$B > 0, (NSf + d)\frac{\partial \theta}{\partial f} + NS\theta < 0$$

$$-\psi N^2S^2A\beta\frac{\partial r}{\partial f}\theta - \psi(NSf + d)NSA\beta\frac{\partial^2 r}{\partial^2 f}\theta - \frac{\partial \theta}{\partial f}\psi(NSf + d)NSA\beta\frac{\partial r}{\partial f} = -\psi(NSf + d)NSA\beta\frac{\partial^2 r}{\partial^2 f}\theta - \psi NSA\beta\frac{\partial r}{\partial f}\left(\frac{\partial \theta}{\partial f}(NSf + d) + NS\theta\right) > 0$$

This paper proves that:

$$\frac{\partial B}{\partial f} < 0$$

Since the inverse function of decreasing function is also decreasing, this paper proves that:

$$\frac{\partial f^*}{\partial B} < 0$$

To prove $\frac{\partial f^*}{\partial B} = 0$ *under the case of no land finance model*

Under this scenario, the population of a city under the spatial equilibrium is given by:

$$L = \frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} (NSf + d)AB^{\beta}\theta}{\bar{U}}$$

Let ψ denote $\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}$. Local government design FAR f to maximize population. The first order condition is:

$$\frac{\partial L}{\partial f} = 0$$

$$\frac{\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} AB^{\beta}}{\bar{U}} \frac{\partial \theta(NSf + d)}{\partial f} = 0$$

The optimal FAR limit f^* is determined by the trade-off between more housing supply and more negative externalities caused by high construction density. Local budgetary revenue *B* will not influence the optimal FAR design under this scenario.

Appendix D: Econometric Appendix

Bias Caused by Reverse Causality

If there is no concern of the reverse causality and omitted variables, β_1 from the following equation will be the unbiased estimate of the budgetary revenue's impact on FAR limit.

$$FAR = \alpha_1 + \beta_1 Budget$$

However, suppose that local budgetary revenue consists of $Budget_1$, which is exogenously determined, and $Budget_2$, which represents local taxes that are correlated with land value and thus FAR limits. As the proof below shows, $\frac{\beta_1}{1-\beta_1\beta_2}$ will represent the OLS estimate of the impact of budgetary revenue on FAR limit, and this coefficient will underestimate the unbiased impact. This is in line with the main empirical findings that the IV estimate is more negative compared with the OLS estimate.

$$Budget = Budget_1 + Budget_2$$

$$Budget_2 = \alpha_2 + \beta_2 FAR$$

$$FAR = \alpha_1 + \beta_1 (Budget_1 + \alpha_2 + \beta_2 FAR)$$

$$FAR = \frac{\alpha_1 + \beta_1 \alpha_2}{1 - \beta_1 \beta_2} + \frac{\beta_1}{1 - \beta_1 \beta_2} Budget_1$$

$$\beta_1 < 0, \beta_2 > 0,\ \frac{\beta_1}{1-\beta_1\beta_2} > \beta_1$$

Bias Caused by Omitted Variable

Another endogeneity concern is caused by uncontrolled local confounding factors. For instance, the density of people living in the pre-existing informal housing will increase the resettlement costs for land acquisition (Fu and Somerville, 2001), and local governments might design higher FAR limits to compensate for these residents. The literature also suggests a positive impact of informal housing on accommodating migrant inflows (Niu *et al.*, 2020), so the density of informal housing might have a positive impact on local economy and budgetary revenue.

If I can control for the population density of the pre-existing informal housing in the following specification, β_1 would be the unbiased estimate of the budgetary revenue's impact on FAR limit.

$$FAR = \alpha_1 + \beta_1 Budget + \beta_2 Density$$

However, the population density of informal housing is not controlled in the main specification due to data availability, and the biased estimate $(\beta_1 + \frac{\beta_2}{\beta_3})$ will therefore underestimate the negative effect of local budgetary revenue. This is in line with this paper's OLS and IV results.

$$Budget = \alpha_2 + \beta_3 Density$$

$$FAR = \alpha_1 + \beta_1 Budget + \frac{\beta_2}{\beta_3}(Budget - \alpha_2)$$

$$FAR = \alpha_1 - \frac{\beta_2 \alpha_2}{\beta_3} + (\beta_1 + \frac{\beta_2}{\beta_3}) Budget_1$$

$$\beta_1 < 0, \beta_2 > 0, \beta_3 > 0, \beta_1 + \frac{\beta_2}{\beta_3} > \beta_1$$