To build above the limit?Implementation of land use regulationsin urban China

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Abstract

This paper studies the implementation of land use regulations in urban China. In particular, we investigate compliance of the floor-to-area ratio (FAR) regulations by rational land developers, using a unique data set of residential land matched with the nearby residential development projects from 30 major Chinese cities. In our sample, developers in more than 20% of cases build above the regulatory FAR limits when they bought the land. Our analysis finds that attractive land location attributes tend to induce an upward adjustment of FAR. Moreover, developers who are more likely to have special relationships with government officials are more likely to build above the limit. We also present evidence that regulatory FAR limits in urban China are much lower than FAR levels maximizing land value, especially for land parcels in relatively more attractive locations. Thus, FAR regulations have imposed a really restrictive constraint on the development of urban land in China.

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Keywords: Floor-to-area ratios; Land development; Implementation; Corruption; Location attractiveness; China

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Introduction

A considerable body of literature shows that in many countries land use regulations have imposed significant restrictions on housing supply (Cheshire and Sheppard, 2002; McMillen and McDonald, 2002; Glaeser and Gyourko, 2003; Glaeser et al., 2005; Bertaud and Brueckner, 2005; Brueckner and Sridhar, 2012). However, the existing literature is generally silent about actual implementation and compliance of land use regulations, thus leaving open the question about the nature and real magnitude of the effects of such regulations. This becomes especially relevant for developing countries like China where regulation compliance should not be taken for granted and corruption in real estate development is rather widespread (Cai, Henderson, Zhang, 2013; Fang, Gu, Zhou, 2014).

In this paper, we study the implementation of land use regulations in urban China by focusing on the floor-to-area ratio (FAR) regulation. FAR is a density regulation for land development, serving as an upper limit on the ratio of the total floor area to the lot size of the land to be developed. FAR regulation is commonly used in many countries, and is considered one of the most important land use regulations. For example, uniform and low regulatory FAR in Mumbai is an important factor behind the prevalence of slums and results in a large welfare loss (Gomez-lbanezand Ruiz Nunez, 2009; Bertaund, 2011; Brueckner and Sridhar, 2012).

We can observe and measure compliance of FAR regulation by comparing the FAR of a land parcel when it is auctioned off with the FAR of the residential development project on the land when it is on the market for sale. Specifically, we identify 854 exactly matched pairs of land parcels and the residential development projects on top of the land in 30 major Chinese cities. In 181 of these 854 cases, land developers built above the regulatory upper limits. The percentage of the upward adjustment is about 21.2%, covering approximately 25.2% of the total land area developed.

To understand the phenomenon of “building above the limit”, we build a simple model of how land developers set FARs in the presence of a regulatory upper limit by extending the framework of DiPasquale and Wheaton (1996). A developer is free to choose FAR as long as it is not higher than the regulatory upper limit. However, if the developer wants to build above the limit, he has to pay an adjustment cost. Informed by our interviews with government officials and land developers, we model the adjustment cost as a function of location attractiveness and corruption. In general, the adjustment cost per extra floor area increases with the land location attractiveness and decreases in corruption. Our model predicts that the developer is more likely to build above the limit if the land is more attractive or if he has a corruptive relationship with government officials.

To estimate our model, we first construct two variables that are essential to the developer’s FAR decision: a continuous variable that measures the location attractiveness for each piece of land and a dummy variable that indicates whether the land sale is likely to involve a corruptive side deal between the developer and government officials. We construct the variable of location attractiveness as an index of value of all relevant location attributes, which includes the distance to the city center, school district, and access to public services such as subway, park and hospital and etc. We consider a land sale likely to be a corruptive one if the land spot was located in an attractive location but sold noncompetitively by auction.

Our estimation yields a few findings. First, location attractiveness has a significant and positive effect on the actual FAR level when the regulatory FAR constraint is not binding. However, its effect becomes weaker when the regulatory constraint becomes binding. This suggests that regulatory FARs are not set purely on the market value of land and adjustment costs are sufficiently significant in preventing developers from changing FARs to their optimal levels. Second, if it is more likely that a land parcel is sold through some corruptive deal, then ex post, its developer is more likely to add more floor areas above the regulatory limit. Thirdly, based on our estimates, we back out the optimal FAR level determined just by market value of land, and find that there exists a large gap between this optimal FAR and the regulatory FAR for more attractive land. Corruption may facilitate an upward adjustment and close up the gap, but in a modest magnitude. This suggests that FAR regulations have imposed a really restrictive constraint in the urban land development of China.

This paper contributes to the literature on the effects of land use regulations (Cheshire and Sheppard, 2005; Glaeser and Gyourko, 2003; Glaeser et al., 2005; Cheshire, 2006; Turner et al., 2014) by showing that regulation compliance is an important factor in evaluating the effects of land use regulations. In this sense, our study echoes with the literature that studies the implementation of environmental regulations by polluting firms (Holland and Moore, 2008; Sigman and Chang, 2011; Cai, Chen and Gong, 2015).

Our paper is also related to the literature on corruption, in particular, corruption in China's real estate sector. The heavily regulated real estate industry and the bureaucratic system in China offer a unique setting for studying corruption (Svensson, 2005). Two recent papers have investigated corruption linked to the real estate development in Chinese cities. Using a dataset on housing mortgage loans from a leading commercial bank in China, Fang, Gu, Zhou (2014) find that bureaucrat from agencies critical to real estate development have enjoyed larger price discounts as house buyers than regular buyers, suggesting that developers may bribe the officials for help in the land development. Cai, Henderson and Zhang (2013) analyze a large dataset of land sale transactions in China and present evidence on corruption in China's urban land auction held by city governments. Using the matched dataset of land sales and ex post developments, our paper compliments theirs by showing that corruption may ease FAR adjustments.

The rest of the paper is structured as follows. Section 2 discusses the background of the urban land markets and FAR regulations in China. Section 3 models the FAR decision of a profit-maximizing developer in the presence a regulatory upper limit and specifies the estimation equations accordingly. We introduce the data for empirical analysis in Section 4, and present the estimation results in Section 5. Section 6 provides some further discussions of preliminary welfare analysis of the FAR regulation. Finally, Section 7 concludes.

2. Background

In China, all urban land is owned by the state. Since 1988, the use rights of vacant urban landhave been allocated through leaseholdsby each city's land bureau. In the 1990s, most use rights allocations were done by "negotiation" between developers and government officials. To control widespread corruption in such negotiated land deals, in 2002 the Ministry of National Land and Resources banned negotiated sales after August 31, 2004.[1] Since then, all urban leasehold sales for private development are done through public auctions. In each city the land auction is held by the local land bureau, with details of all transactions posted to the public on the internet. Although public auction is generally viewed as a way to prevent corruption in land allocations, there is still a wiggle room. Two-stage auction (called *guapai* in Chinese) and English auction (called *paimai* in Chinese) are two main types of auction used by land bureaus. As Cai, Henderson and Zhang (2013) show, a corruptive land bureau official tends to select two-stage auction for the piece of land in which her partner developer is interested. The partner

[1] More than 90 percent of the land sales in our data were done after 2004.

developer can signal that this land parcel is already taken by bidding at the reserve price at the beginning of the first stage of the auction and hence significantly deter entry of other competitors into auction.

The cityland bureau does long-term land use planning with aims of promoting “rational” land use, guarding “public interests,” and protecting historic heritages and natural resources. Guided by these plans, each year a land use allocation committee decides the use type and development restrictions (e.g., the regulatory FAR limit, building height, green area rate, etc.) before land parcels are turned over to the land bureau for auction. This committee consists of members such as the mayor and key figures of relevant local government bureaus, such as the land bureau and the urban planning and development bureau.

FAR regulation is one of the most important land use regulations in urban China. By law, any land parcel to be auctioned off must be designated a regulatory FAR level. Also, after the land is developed, the city’s planning bureau must do an official inspection on the residential project before it is to put on the market for sale, in order to make sure compliance of the FAR regulation. In most of the cases, the FAR regulation takes the form of an upper bound constraint on the ratio of a building’s total floor area to the lot size on which the building is to be constructed. Lower bound constraint cases are very rare and almost always not binding in our exactly matched sample. So we focus on the upper bound constraint of FAR in this paper.

FAR is not equivalent to building height. A developer can achieve a higher FAR by reducing open space and building more densely on a given piece of land without increasing the building height. A developer can freely choose the FAR level as long as it is not higher than the regulatory upper limit. However, if a developer wants to build above the FAR constraint, he must file an application for the adjustment of FAR to the government first. Although the details of such a process vary by city, in general it must go through the following steps guided by the Urban and Rural Planning Law[2]: first, the developer submits an official application to the city's planning bureau. The planning bureau then conducts the first round review of the case. In reviewing, the planning bureau coordinates with other government branches (e.g., the Development and Reform Commission, the land bureau, the transportation bureau, the environment protection bureau and the cultural heritage bureau and etc.) to make sure the proposed adjustment does not violate any law or regulation. If the case passes the first round review, then as the second step, the planning bureau asks for evaluations on the potential costs and benefits of the proposed adjustment from some independent appraisers. The selection of outside experts must follow certain rules. Thirdly, the planning bureau posts the application, along with its own review report and the outside evaluation reports, to the public for at least 30 days. Meanwhile, the planning bureau seeks opinions from relevant parties, especially those who may be affected by the proposed adjustment. An official hearing may be held if necessary. Finally, if the planning bureau decides to pass the case, it submits a formal report to the upper level government for final approval. The above application process is rather complicated and time-consuming. Typically it takes seven to eight months. This imposes a significant cost on developers if they want to do FAR adjustments.

Note that obtaining approval of FAR adjustment from authorities is essential for developers who want to adjust FAR. Without permission, he is not legally allowed to sell the housing units on the market. After obtaining the final approval, the developer then needs to pay certain amount of land compensation payment to the city's land bureau for the additional floor areas above the original limit. Detailed rules of compensation are set by each city's land bureau and vary by city.

[2]In 2012, the Ministry of Housing and Urban-Rural Construction issued a provision on the adjustment of regulatory FARs, based on the Urban-Rural Planning Law.

In general, the compensation payment is positively associated with the market value of the land parcel estimated by an independent land appraiser. Sometimes, if the developer promises to provide extra public services such as paving a public road, then part or all of the compensation payment may be waived.

The overall cost of FAR adjustment is thus composed of the costs associated with the application process and the land compensation fee. If the developer has no connection with the government officials, the adjustment cost could be very high. However, with some corruptive deal, the government can green-light the upward adjustment of FAR by the developer at a relatively lower cost. For example, permission can be granted more easily and quickly. The assessment of land compensation fee for the added floor areas can favor the developer to reduce his direct adjustment costs. Also, there is quite a bit wiggle room in measuring how many extra floor areas have been added by the developer above the FAR upper limit ex post.

3. Theoretical Framework and Estimation Specification

3.1 Theoretical Framework

Our model builds upon the benchmark model elaborated by DiPasquale and Wheaton (1996). A developer sets FAR to maximize the profit from development (i.e., the value per land unit). There exists a trade-off for the developer. On the one hand, a greater FAR raises gross profit by increasing the number of housing units built on each unit of land. On the other hand, a greater FAR reduces the housing price because consumers are willing to pay less as density increases. Meanwhile, as FAR increases, construction costs rise. Furthermore, in case of an upward deviation from the regulatory upper limit, there is an adjustment cost. To specify the value per land unit as a function of FAR, we first write down the hedonic equation for the housing price per floor area, as well as the construction cost per floor area and the additional adjustment cost associated with extra FAR above the limit.

The hedonic equation for the housing price per floor area is

(1) $p = \alpha + \beta F$,

where α denotes the location attractiveness of land, which represents the collective value of all relevant location attributes. F denotes the actual FAR, and β represents the marginal reduction in housing price per floor area as FAR is increased ($\beta < 0$).

The functional form of the cost per floor area in housing construction is as follows:

(2) $C = \mu + \tau F$,

where μ represents a basic cost of construction per floor area, and τ represents the incremental cost as FAR is increased ($\mu > 0$, $\tau > 0$).

Putting extra FAR above the regulatory upper limit, ($F - F_R$), incurs additional adjustment cost. Such cost typically rises with the location attractiveness (α). With corruption, theadjustment cost may be lowered. Let R be a dummy variable that indicates whether the developer has some corruptive deal with government officials. Therefore, the general functional form of adjustment cost per extra floor area can be written as follows:

(3) $\psi(\alpha, R)$, if $F > F_R$; zero, otherwise,

where $\psi_\alpha > 0$,reflecting that the land compensation fee increase with land attractiveness; and $\psi(\alpha,1) < \psi(\alpha,0)$.

The developer chooses FAR to maximize the value per land unit. Based on (1), (2), and (3), his objective function is

$$\begin{aligned} & Max_F \; p_l = (p-C)F - I(F>F_R)\cdot\psi(\alpha,R)(F-F_R) \\ (4) \qquad & = (\alpha-\mu)F - (-\beta+\tau)F^2 - I(F>F_R)\cdot\psi(\alpha,R)(F-F_R), \\ & \quad s.t. \quad F \geq 0 \end{aligned}$$

where I is an indicator function. Assume that $(\alpha-\mu)>0$. Solve the maximization problem specified above, we have the FAR that maximizes the value per land unit as follows:

$$(5)\; F = \begin{cases} \bar{F}_0 \equiv (\alpha-\mu)/(2(-\beta+\tau)) & \text{if } F_R \geq \bar{F}_0 \\ F_R & \text{if } \bar{F}_1 \leq F_R < \bar{F}_0 \\ \bar{F}_1 \equiv (\alpha-\mu-\psi(\alpha,R))/(2(-\beta+\tau)) & \text{if } F_R < \bar{F}_1 \end{cases},$$

where $\bar{F}_0$ is the level that maximizes the value per land unit in the absence of regulations, and $\bar{F}_1$ is the level that maximizes the function $(\alpha-\mu)F-(-\beta+\tau)F^2-\psi(\alpha,R)(F-F_R)$. Assume $1-\psi_\alpha>0$; otherwise we would have a trivial case where it is never optimal for a developer to go above the upper limit of FAR. $\bar{F}_0$ and $\bar{F}_1$ both increase with location attractiveness α. However, $\bar{F}_1$ increases with α at a smaller rate than $\bar{F}_0$ since $\psi_\alpha>0$. In addition, $\bar{F}_1$ is higher if R equals one; i.e., if with the help of some corruptive deal.

The two variables α and R are key determinants in the FAR decision. They both vary by land, causing a difference in the decision whether to comply with the regulatory upper limit (F_R) across developments. In particular, when α is relatively low, $\bar{F}_0$ is lower than F_R and therefore it is optimal for the developer to choose an FAR level below F_R. As α rises, $\bar{F}_0$ becomes larger than F_R; however, before α gets high enough, the adjustment cost will prevent the developer from building above the limit. So the developer just sets the FAR at the upper limit. Finally, induced by a sufficiently high α, $\bar{F}_1$ exceeds F_R; it is then optimal for the developer to set the FAR above the upper limit F_R even with adjustment costs.

To investigate the effects of both location attractiveness (α) and corruption (R) on the decisions of private developers regarding whether to comply with FAR constraints, we estimate the model parameters in the functions of $\bar{F}_0$ and $\bar{F}_1$ shown in (5). Using these parameter estimates, we may also predict the FAR levels under different scenarios such as absent of regulation and absent of corruption.

3.2 Estimation specifications

Our estimation specifications closely follow the theoretical formulas presented in Section 3.1. For estimation purpose, we write $\bar{F}_0$ and $\bar{F}_1$ for each observation i as functions of α, R, and error terms, respectively:

(6a) $\bar{F}_{0i} = \eta_{00} + \eta_0 \alpha_i + u_{0i}$

(6b) $\bar{F}_{1i} = \eta_{00} + \eta_0 \alpha_i - \theta \psi_i(\alpha, R) + u_{1i}$,

where $\eta_0 \equiv 1/(2(-\beta + \tau))$, $\theta \equiv 1/(2(-\beta + \tau))$, and $\eta_{00} \equiv -\mu/(2(-\beta + \tau))$. The error terms u_{0i} and u_{1i} capture the unobserved heterogeneity across developers in the costs of construction as well as their private value of location amenities. Meanwhile, u_{1i} also captures the unobserved variation in adjustment cost when an upward adjustment occurs. The maximum likelihood estimation is used to deal with the nonlinear nature of the FAR decision in the presence of an upper limit shown in (5). To implement the MLE, we impose the following joint normal distribution assumption on u_{0i} and u_{1i}:

(7) $\begin{pmatrix} u_{0i} \\ u_{1i} \end{pmatrix} \sim \mathrm{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_0^2 & \rho\sigma_0\sigma_1 \\ \rho\sigma_0\sigma_1 & \sigma_1^2 \end{bmatrix} \right)$

In addition, we assume a linear functional form of $\psi(\alpha, R)$:

(8) $\psi_i(\alpha, R) = \psi_0 + \psi_1 \alpha - \chi R_i$,

where $\psi_1 > 0$ and $\chi > 0$. In this functional form, corruptive deals do not affect the rate at which the land compensation fee increases with α; i.e., ψ_1 is constant. This is a plausible assumption because in practice the land compensation fee is typically proportional to the market value of the land parcel, which is evaluated by some independent appraiser. Therefore, we believe that there is little room for corruption to erode in here.[3] Substitute this adjustment cost expression into equation (6b) and re-arrange terms, we obtain a new version of equation (6b) as follows:

(6b') $\bar{F}_{1i} = (\eta_{00} - \theta\psi_0) + (\eta_0 - \theta\psi_1)\alpha_i + \theta\chi R_i + u_{1i}$.

Let $\{F_i : i = 1, 2, ..., N\}$ be a random variable following the optimal FAR choice defined by (5). From equations (6a) and (6b'), we derive the data generating function for F_i given α_i and R_i:

$$(9)\quad F_i = \begin{cases} \bar{F}_{0i} = \eta_{00} + \eta_0\alpha_i + u_{0i} & \text{if} \quad u_{0i} \le -\eta_{00} - \eta_0\alpha_i + F_{Ri} \\ F_{Ri} & \text{if} \;\; u_{1i} \le -A_1 - \eta_1\alpha_i - \lambda R_i + F_{Ri},\, u_{0i} > -\eta_{00} - \eta_0\alpha_i + F_{Ri} \\ \bar{F}_{1i} = A_1 + \eta_1\alpha_i + \lambda R_i + u_{1i} & \text{if} \;\; u_{1i} > -A_1 - \eta_1\alpha_i - \lambda R_i + F_{Ri} \end{cases}$$

where $A_1 \equiv (\eta_{10} - \theta\psi_{00})$, $\lambda \equiv \theta\chi$, $\eta_0 \equiv 1/(2(-\beta + \tau))$, and $\eta_1 \equiv (1 - \psi_1)/(2(-\beta + \tau))$ .We expect both η_0 and η_1 to be positive, with η_1 smaller than η_0 due to the fact that the land compensation part of the adjustment cost increases with α. We also expect λ to be positive because corruption lowers the adjustment cost (i.e., $\chi > 0$ shown in (8)). Estimation details are presented in appendix.

4. Data

[3]As a robustness check, later we also include an interaction term between α and R in the regressions. This term turns out to be statistically insignificant.

Our empirical analysis utilizes a unique data set that matches 6,035 historically transacted residential land parcels with 4,726 nearby newly-built residential development projects (referred to as RDP's hereafter) in 30 major Chinese cities.[4]

4.1 Land transaction data

We focus on residential land in this paper. For each land sale, the land bureau provides detailed information and posts it on its official website www.landlist.cn. The basic information includes the use type, land area, reserve price, sales price, sale date if the sale is completed, regulatory lot size for construction, regulatory total floor area, auction type, etc. We collect data for 9,394 completed auctions from 30 cities between 2002 and 2012. 92% of our land sales were done after 2004. For each land sale, we calculate the regulatory FAR as regulatory total floor area divided by regulatory lot size for construction, which is considered to be the upper limit imposed on FAR for land development.For part of the land parcels in our sample, detailed information on regulatory FARs specified by local land bureaus are available. For these land parcels, our calculated regulatory FARs overlap with the government specified ones very well. Additionally, we obtain the geographic coordinates from www.Soufun.com for each land parcel. Using the coordinates, we calculate for each land parcel the distance to the city center, and the distance to the nearest subway stop.[5][6]

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[4]These 30 cities are: Beijing, Changchun, Changsha, Chengdu, Chongqing, Dalian, Guangzhou, Ha'erbin, Haikou, Hangzhou, Hefei, Huhehaote, Jinan, Kunming, Nanchang, Nanjing, Nanning, Ningbo, Qingdao, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Suzhou, Taiyuan, Tianjin, Wuhan, Wuxi, Xi'an, and Zhengzhou.

[5]We use the coordinates of 1992 light center within 2010 city proper boundaries from Baum-Snow et al. (2014) to identify the city center. They suggest that despite the fact that light has been increasing enormously during the past two decades, 1992 light centers are still brightest in 2009.

[6]Among the 30 cities of our sample, Beijing, Chengdu, Chongqing, Guangzhou, Shanghai, Shenzhen, and Suzhou have subway systems by 2012.

For eleven cities that have more than 300 land transactions in our full sample, Table 1 reports the summary of statistics of land attributes by city. Panel A in Table 1 describes the city level characteristics such as the actual population size and the annual population growth rate based onthe 2000 and 2010 Chinese population censuses. Panel B in Table 1 shows the characteristics of residential land parcels by city in our full sample. Compared with cities in the central and western regions (i.e., Chengdu, Wuhan, and Xi'an), cities in the eastern region (i.e., Shanghai, Beijing, Tianjin, Hangzhou, Nanjing, Dalian, Qingdao, and Wuxi) have higher population growth rates but lower regulatory FARs on average. Within each city, a large variation of the regulatory FAR exists. In addition, the distance to the city center also varies largely across land parcels within each city, suggesting a spread-out spatial distribution of land development.

4.2 Residential development project (RDP)and matched data sets

We collect the information on RDP that has new property for sale as of May 2012 from www.Soufun.com.For each RDP, we have the average housing price per square meter of floor area, which is referred to as RDP price in this paper, the actual FAR, a dummy variable indicating whether the units in RDP are decorated, green space ratio, and the geographic coordinates as of May 2012.

Using the coordinates of both land parcels and RDP's, we draw a ring that extends out to 1.5 kilometers from the geographic centroid of each land parcel and match all RDP's located in this ring to the land parcel. The land-RDP pairs thus matched are referred to as the generally matched pairs. In total, we match 6,035 residential land parcels with 4,726 RDP's. The location attractiveness of each land is inferred from the prices of RDP's located within the 1.5 km ring of the land. We do not use the actual land sale prices to measure the land location attractiveness because these prices may be corrupted and hence may not reflect market values (see Cai, Henderson, Zhang, 2013).For each RDP, we also calculate the distance to the city center, and the distance to the nearest subway stop using coordinates information. Panel D presents the summary statistics of housing characteristics for all the RDP's in the generally matched sample. We also report the summary of statistics for all the land in the generally matched sample in panel C of Table 1, for the sake of comparison with panel B. They have similar patterns.

From the sample of generally matched pairs, we identify 854exactly matched pairs across 27 of the 30 cities.[7]An exactly matched pair contains a land parcel and a RDP that is just built on this piece of land. In Figure 1, the left panel plots the regulatory upper limits of FAR[8]and the actual FARs of these exactly matched pairs, and the right panel shows the density distribution of the difference between these two levels.181pairs of the 854 have their actual FARs surpass the upper limits, while the rest has their actual FARs lie equal to or below the upper limits.In 21 of the 854exactly matched pairs, a regulatory lower bound is also set, which is presumably to restrict the construction of low-density houses such as luxury villas. Only threeof the 21 cases have their actual FARs below their regulatory lower bounds, meaning the lower bound of FAR is mostly a non-binding constraint. Therefore, in this paper, we focus on the FAR upper limit constraint.

In ourexactly matched sample,more recently developed projects tend to have fewer upward adjustments, which may be a result of the recent anti-corruption movement in the real estate market. In particular, among RDP's constructed on land parcels sold before 2008, more than 25%

[7]They are Beijing (89), Changchun (19), Changsha (9), Chengdu (70), Dalian (63), Guangzhou (18), Ha'erbin (17), Haikou(4), Hangzhou (50), Huhehaote (2), Jinan (8), Kunming (6), Nanchang (39), Nanjing (61), Nanning (1), Ningbo (19), Qingdao (44), Shanghai (27), Shenyang (26), Shenzhen (16), Shijiazhuang (13), Taiyuan (10), Tianjin (50), Wuhan (69), Wuxi (63), Xi'an (33), and Zhengzhou (28). Numbers of observations are in parentheses.

[8]For this exactly matched sample, we are able to find detailed information on regulatory FARs specified by local land bureaus.

involve an upward adjustment of FAR (i.e., 14 of the 23 in 2003, 10 of the 21 in 2004, 6 of the 26 in 2005, 21 of the 70 in 2006, 28 of the 104 in 2007). This percentage of upward adjustment has dropped to around 15% since 2008 (i.e., 15 of the 91 in 2008, 33 of the 234 in 2009, 36 of the 204 in 2010). In addition, the RDP's that have new property for sale as of May 2012should be developed more recently relative to all the RDP's developed in the past decade. Therefore, the percentage of upward adjustment based on our data (i.e., 21.2%) can be lower than the overall percentage that people would expect of all the residential projects developed in the past decade.

4.3. Other data

We hand-collect the information on the turnovers of party secretary for each city between 2000 and 2012from each city's government website. The information includes the month of turnover, and the names of the old and new party secretaries. This data sheds light on the political environment for each city over our sample period and helps us provide supporting evidence to our corruption indicator discussed in details later.

5.Estimation results

5.1 Measure of land location attractiveness

We measure the location attractiveness of each land parcel based on the prices of RDP's located in the neighborhood of the land. In particular, we first estimate the location attractiveness of each RDP which captures the collective value of the attributes in the neighborhood where the RDP is located, controlling for the effects of the characteristics of RDP itself (i.e., the actual FAR, green space ratio, and decoration degree) on RDP prices. We then measure the location attractiveness of each land parcel by taking the average of location attractiveness of all the RDP's located in the 1.5 km ring of the land parcel.

Conceptually, the relationship between the RDP price per floor area and RDP characteristics follows the hedonic equation for housing prices presented in the theory part. Empirically, we specify the logarithm of the RDP price per floor area, $\log(p_j)$, as follows:

(10) $\log(p_j) = Z_j\gamma + \kappa_i + \varsigma_j$,

where Z_j represents the observed characteristics of RDP j, including the logarithm of the actual FAR, the green space ratio, and the decoration degree (one indicates that the housing units in the RDP are fully decorated; zero means otherwise). κ_i is the ring fixed effect, where i indicates the 1.5 km ring around land parcel i in which RDP j is located. ς_j describes the unobserved determinants of RDP prices. The location attractiveness of RDP j then can be calculated as

(11) $\hat{\alpha}_j = \log p_j - Z_j\hat{\gamma}$,

where $\hat{\gamma}$ is the estimate for γ in equation (10).

The empirical challenge for identifying γ is that the observed RDP characteristics may be correlated with some unobserved location attributes that affect RDP prices. Therefore, we use a ring fixed effect κ_i to control for the neighborhood characteristics within the 1.5km ring around land parcel i in which the RDP is located. That is to say, we use the variations in $\log(p_j)$ and Z_j within the same 1.5km ring to identify γ. The identification assumption is that, within the ring, other unobserved factors in the error term are uncorrelated with Z_j.

We run hedonic housing price regressions using land-RDP pairs. Each observation in the regression is a matched land-RDP pair from the generally matched sample. About 75% of the 6,035 land parcels in the generally matched sample have multiple RDP's falling in their 1.5 km rings each. The estimation results are robust to dropping those land parcels that have only one RDP located in their 1.5 km rings.

Table 2 reports the regression results. Column 1 includes the logarithm of actual FAR (log FAR), green space ratio, decoration degree, and city fixed effects. Because consumers are willing to pay less per housing unit as density increases, the coefficient on log FAR is expected to be negative. The positive sign for log FAR in column 1(0.140 with *t* at 12.70) suggests that the actual FAR could be correlated with some desirable location attributes left in the error term, such as the proximity to the city center, a convenient access to the public transportation infrastructure, or good school quality. Therefore, in column 2, we further include the logarithms of distance to city center and distance to the nearest subway stop in the regression to partially control for the relevant location attributes. Controlling for these characteristics significantly reduces the magnitude of the estimated coefficient on log FAR, but the coefficient is still statistically insignificant (-0.001 with *t* at -0.07).

In column 3, we include the ring fixed effects to control for the unobserved location attributes as specified in equation (9). The estimated effect of log FAR becomes statistically significant and much larger in size at-0.066 with *t* at -4.88. Meanwhile, the estimated coefficient on green space ratio becomes statistically insignificant, and the magnitude of the estimated coefficient on decoration degree drops, too. Note that our estimate for the coefficient on log FAR is larger in absolute value than the estimate reported in Wu et al. (2013) which is at -0.01.[9] Without fully controlling for the unobserved location attributes, the marginal effect of FAR on housing prices may be underestimated.

[9]Wu et al. (2013) use a transaction data set of new units for a typical large Chinese city. The sample includes 539,067 newly-built non-landed condominium units in 2,534 residential developments sold between 2004 and 2009 in this city.

Using the estimates in column 3, we calculate the location attractiveness of each RDP. The location attractiveness of each land parcel then is measured with the average value of location attractiveness across all RDP's falling in the 1.5 km ring around the land. Finally, we standardize the landlocation attractiveness to have a mean of zero and a standard deviation of one.

Next we check whether the constructed land location attractiveness indeed reflects the value of location attributes around each land parcel. We run regressions of the constructed land location attractiveness on various observed location attributes for all land in the generally matched sample. Column 1 of Table 3 shows that the proximities to the city center and subways are positively associated with the location attractiveness of land. For a subset of sample, we also have the information on the reserve price of the land parcel, which is set by an outside committee who uses a formula of an independent land appraiser and may reflect some unobserved location attributes.Column 2 further includes log land reserve price. While the other coefficients remain roughly stable, the estimated location attractiveness is additionally associated with the variation in reserve price. Column 3 shows that, for the sample of the 854 exactly matched pairs, the way how location attractiveness is correlated with the observed location attributes resembles that for all land in the generally matched sample (column 1). Therefore, we believe that the estimated location attractiveness of land can well summarize the collective value of location attributes within the 1.5 km ring around each land parcel.

5.2 Indicator of corruption

Because we cannot observe corruption per se, we construct a dummy variable to indicate whether there is likely a corruptive deal between the developer and governmental officials. Particularly, we investigate the historic land sale information to check if there exists any sign of corruption when the land was auctioned off. If there is, then it often comes with favoring treatment to the developer in the ex post land development which will reduce the adjustment cost of an upward adjustment of FAR, according to Cai, Henderson, Zhang (2013).

The corrupt government official may help her partner developer win the land by deterring the entry of other competitors into the auction. As such, we first compare the land reserve price and land sale price for each piece of land in the auction. If the ratio of sale price to reserve price is below 1.005, then we identify this sale as a noncompetitive sale following Cai, Henderson, Zhang (2013). Because a land parcel with poor location attractiveness (a "cold" spot) may attract few bidders, noncompetitiveness alone may not well indicate a corruptive land auction. Therefore, to indicate the existence of corruption in the land sale, we further interact the noncompetitive dummy with a dummy variable indicating whether the land parcel's location attractiveness is above certain percentile in the distribution of the estimated α. If such a "hot" land parcel generates no competition in a public land auction, then it is very likely that the land auction is corrupt. Specifically, we define the corruption indicator as $R_i \equiv NC_i * Top_{i20}$, where NC_i is a dummy for noncompetitive sale and Top_{i20} is a dummy indicating whether land parcel i lies at top 20 percentile or above in the distribution of the estimated α within the sample of generally matched pairs. This method is similar to the practice in the literature that uses ex post bidding prices to detect illegal activities in public auctions (Porter and Zona, 1993). We use 20 percentile in the main regressions, but present results using other percentiles as robustness checks later.

To provide supporting evidence to our corruption indicator, we investigate the relationship between the likelihood of a land parcel being sold via a noncompetitive sale and the political turnover of the party secretary in the city.[10]Using all land in the generally matched pairs, we run a linear probability regression of land being sold via a noncompetitive sale on a political dummy that indicates if the land transaction occurs one quarter before a new party secretary takes office in the city (1 if yes; otherwise zero).According to Cai, Henderson, Zhang (2013), the political uncertainty rises right before the transition of party secretaries in a city and, thus, during such a period, the city's government officials are more discreet than usual and they try hard to prevent any clue of corruption that may involve themselves in. Therefore, we expect a negative effect of the political dummy on the probability of a noncompetitive sale. We also control for the location attractiveness of land in the regression because the land parcel with poor local amenities is less attractive to potential bidders and thereby more likely to sold through a noncompetitive sale.

Column 1 of Table 4 reports the results.As expected, the coefficient on the political dummy is -0.074 with t at -3.03, which implies that there exists a significant drop in the chance of being sold through a noncompetitive sale during a political environment that is more adverse towards corruption. The location attractiveness has an expected effect as well, which is -0.031 with t at -3.22.In column 2, we additionally include an interaction term between the political dummy and location attractiveness of land in the regression. Its coefficient is significantly negative at the 10% level. That is to say, in a political environment that is more adverse towards corruption, the drop in the chance of being sold via a noncompetitive sale is greater for more attractive land parcels. This result suggests a "hot" spot is more likely to involve corruption than a "cold" spot, which lends support to our way of constructing the corruption indicator. It also echoes with Cai, Henderson, Zhang (2013) who finds the hot spots are more likely to be selected into two stage auction, an auction format that is particularly susceptible to corruption. Columns 3 and 4 of

[10]The party secretary in a city is the highest ranked city official acting as "chair of the board," while the city major is the chief executive officer more involved in the details of decisions.

Table 4 also report the results from a Probit model. They are similar to the results in columns 1 and 2, respectively. In all columns of Table 4, we control for the land characteristics (i.e., log land area, and land mixed use type dummies), land sale season, land sale year, and city fixed effects. Because location attractiveness α is a generated variable, we calculate the standard errors of all regressions using the bootstrap with 2,000 replications.

5.3 Effects of location attractiveness and corruption on FAR decision

Table 5 reports the MLE results corresponding to the FAR decision specified in equation (9). The estimation is based on 643 observations from the exactly matched sample for which we have information on reserve prices to construct our corruption indicator. Standard errors are calculated on the basis of 2,000 bootstrap replications because α is a generated regressor. In all regressions, we control for land characteristics (i.e., log land area, and land mixed use type dummies), land sale season, and a linear year trend.

Columns 1 and 2 in Table 5 present the baseline specification results. Column 1 corresponds to the specification of $\bar{F}_0$ and column 2 corresponds to the specification of $\bar{F}_1$ in equation (9). We first investigate the effects of α on $\bar{F}_0$ and $\bar{F}_1$, which correspond to η_0 and η_1 in (9), respectively. According to the theory, $\bar{F}_0$ and $\bar{F}_1$ both increase with α. However, because the adjustment cost increases with α at rate ψ_1 as shown in (8), $\bar{F}_1$ increases with α at a slower rate than $\bar{F}_0$. Therefore, we expect that $\eta_0 > \eta_1 > 0$. Consistent with the model, the estimate of η_0 is 0.110 with t at 2.481 as shown in column 1, whereas the estimate of η_1 is 0.032 with t at 0.351 as shown in column 2.

Next, we examine the effect of corruption (R) on $\bar{F}_1$, which corresponds to λ in equation (9). A corruptive deal ex ante reduces the ex post adjustment cost and hence encourages a greater upward adjustment of FAR. As expected, the estimated λ is 0.624 with t at 2.03 as shown in column 2.

The empirical evidence here suggests that attractive location attributes tend to induce an upward adjustment of FAR, but the associated adjustment cost prevents the developer from doing so. However, with some corruptive deal, the adjustment cost could be reduced to some extent and, thus, the developer may choose to put more extra floor area above the regulatory limit. According to the theory, the corruption indicator R should have no effect on $\bar{F}_0$. Thus in our baseline specification for $\bar{F}_0$, there is no corruption indicator included. To check the validity of this specification, we include R in the specification of $\bar{F}_0$ and run the MLE again. Columns 3 and 4 report the results. The estimates of η_0, η_1, and λ are affected by little. As expected, the partial effect of R on $\bar{F}_0$ is statistically insignificant with a small magnitude (0.012 with t at 0.077).

In the functional form of adjustment cost (8), we assume that corruption does not affect the rate at which the adjustment cost increases with α (i.e., ψ_1 does not vary by R). To verify this assumption, we also try adding the interaction term between α and R into the specification of $\bar{F}_1$ to capture the effect of corruption in reducing ψ_1. The estimated coefficient on interaction term is small and statistically insignificant, which lends support to the assumption imposed on the functional form of the adjustment cost. We do not report this result in the paper but may provide it upon request.

One concern is that some city natural amenities (e.g., the climate and geographic characteristics) may affect local housing supply (Saiz, 2010). Meanwhile, the differentials in natural amenities across cities may also be associated with variations in location attractiveness

(Gyourko, Mayer, and Sinai, 2013). To address this concern, we additionally control for the city-level natural amenities (i.e., the number of days with rain above 10mm, the minimum temperature, the maximum daily temperature range, sunshine exposure index, the roughness of land surface, and the range of land elevation) in the regressions. The results corresponding to the specifications used in columns 1 to 4 are reported in columns 5 to 8, respectively. There is a modest increase in the size of the estimate of the coefficient on α, for both $\bar{F}_0$ and $\bar{F}_1$, but the estimate of η_1 is still statistically insignificant with a smaller magnitude than that of η_0. Meanwhile, the size of the estimate of the coefficient on R_i slightly rises. In general, the results are robust to including the city-level natural amenity variables.

The estimation model implies that the variance of random term u_{1i} in $\bar{F}_{1i}$ (i.e., σ_1^2) is greater than that of u_{0i} in $\bar{F}_{0i}$ (i.e., σ_0^2) because the former additionally includes the unobserved variation in adjustment cost when an upward adjustment occurs. Consistent with this, the estimates of σ_0 and σ_1 are around 0.7 and 1.3, respectively. Moreover, in the estimation, we impose ρ to be one, but investigate results by allowing ρ to vary between 0 and 1. Results show that the log likelihood function strictly increases in the value of ρ.

5.4 Robustness checks: alternative corruption indicators

Different cutoff percentiles

Top 20 percentile is used as the cutoff point when constructing the corruption indicator for main analysis. We also experiment with other percentiles and construct alternative corruption indicators accordingly. We run the MLE following the specification used in columns 5 and 6 in Table 5. The results are presented Table 6. The estimates of the coefficients on α in both the specifications of $\bar{F}_0$ and $\bar{F}_1$ (i.e., η_0 and η_1) are insensitive to applying these alternative corruption indicators. The estimated coefficients on R in the specification of $\overline{F}_1$ are 0.921 (t at 1.78), 0.668 (t at 2.14), and 0.247 (t at 1.01) for the top 10, 20, and 30 percentiles. This pattern is in fact consistent with the fact that a "hot" spot is more likely to involve corruption than a "cold" spot. In other words, when the cutoff percentile gets closer to the top, if the corruption indicator equals 1, then it is more likely that there exists some corruptive deal. As we expand the percentile to include land with relatively poor local amenities, we cover more of those that are sold noncompetitively but involve no corruptive deal.

Land auction format as indicator

Cai, Henderson, Zhang (2013) find that the two-stage auction format is more likely to be selected by a corrupt government official to deter the entry of other potential bidders into auction, thereby enhancing the chances that the corrupt developer wins the land. As such, we use the probability of being sold through a two-stage auction to indicate corruption. The probability is predicted from a linear probability model with RHS variables being the political dummies and land characteristics similar to those used in Cai, Henderson, Zhang. The estimated coefficient of such a corruption indicator on $\overline{F}_1$ is 0.870 with t at 2.02. Therefore, a corruptive deal not only helps the developer win the land in auction, but also comes with ex post help in the form of more tolerant treatment towards adding extra floor area above the regulatory FAR limit, which is consistent with the theory of Cai, Henderson, Zhang. The estimated effect of α on $\overline{F}_0$ and $\overline{F}_1$ is similar to the main results presented in Table 5.

6. Discussions

How restrictive is the regulatory burden on private land developers imposed by FAR constraints? To what extent has corruption loosened the restriction and made the actual FAR levels more responsive to market incentives? In this section, we generate predictions of the FAR levels under different scenarios to answer these questions, using parameter estimates from columns 5 and 6 of Table 5. Specifically, the predicted FAR chosen by developers follow the specifications defined by equation (9), with "^" denoting predicted values:

$$(12a)\quad \hat{F}_i = \begin{cases} \hat{\bar{F}}_{0i} = \hat{\eta}_{00} + \hat{\eta}_0\alpha \quad if \ F_{Ri} \geq \hat{\bar{F}}_{0i} \\ F_{Ri} \quad if \ \hat{\bar{F}}_{1i} \leq F_{Ri} < \hat{\bar{F}}_{0i} \\ \hat{\bar{F}}_{1i} = \hat{A}_1 + \hat{\eta}_1\alpha_i + \hat{\lambda}R_i \quad if \ F_{Ri} < \hat{\bar{F}}_{1i} \end{cases}$$

In addition, we generate the predicted FAR in the absence of corruption as

$$(12b)\quad \hat{F}_i^{AC} = \begin{cases} \hat{\bar{F}}_{0i} = \hat{\eta}_{00} + \hat{\eta}_0\alpha \quad if \ F_{Ri} \geq \hat{\bar{F}}_{0i} \\ F_{Ri} \quad if \ \hat{\bar{F}}_{1i}^{AC} \leq F_{Ri} < \hat{\bar{F}}_{0i} \\ \hat{\bar{F}}_{1i}^{AC} = \hat{A}_1 + \hat{\eta}_1\alpha_i \quad if \ F_{Ri} < \hat{\bar{F}}_{1i}^{AC} \end{cases},$$

and the predicted FAR in the absence of regulatory limits as

$$(12c)\quad \hat{\bar{F}}_i^{AR} = \hat{\eta}_{00} + \hat{\eta}_0\alpha_i \, .$$

For each of the land observations in the exactly-matched sample, Figure 2a plots the actual FAR, F_i in the solid line and the predicted $\hat{F}_i$ in the short-dash line as functions of land location attractiveness. From this figure, one can see that our model fits the data very well.

Figure 2b plots the predicted $\hat{F}_i^{AR}$ absent of regulation in the long-dash line and the regulatory F_{Ri} in the dash-dot line, against land location attractiveness. Figure 2b shows that there is a large gap between the developers' optimal FAR levels just determined by land attractiveness (i.e., $\hat{F}_i^{AR}$) and the regulatory limits set by authorities (i.e., F_{Ri}). Furthermore, this gap widens with the land attractiveness. In particular, $\hat{F}_i^{AR}$ is on average 23% higher than F_{Ri}, while for the land developments above the median attractiveness, this percentage rises to 28%. We also calculate

$\hat{F}_i^{AR}$ for all land in the generally matched sample. For the expanded sample, $\hat{F}_i^{AR}$ is on average 23% higher than F_{Ri}, while for the land developments above the median attractiveness , this percentage rises to 32%. Therefore, we consider that the FAR restrictions in urban China have deviated from market incentives reflected by land attractiveness to a large extent, especially for land in relatively more attractive locations. This finding is consistent with the raw data pattern shown in Table 1 that both the average and top 90 percentile of the regulatory FAR limits in the cities located in the eastern region are significantly lower than those in the central and western regions, despite larger population size and greater population growth in the east.

In Figure 2b, we also plot the actual F_i in the solid line, and the predicted $\hat{F}_i^{AC}$ absent of corruption in the dotted line. One can see that the actual FAR levels (F_i) surpass the regulatory limits (F_{Ri}) only for land parcels in relatively more attractive locations, consistent with the theory. For the range of location attractiveness where upward adjustments occur, the FAR levels that would have been selected in the absence of corruption ($\hat{F}_i^{AC}$) mostly lie at or below the regulatory limits. This indicates that the upward adjustments of FAR would have not occurred had no corruption existed. However, compared with the gap between $\hat{F}_i^{AR}$ and F_{Ri}, such adjustments are modest in magnitude, implying that FAR regulations have imposed a really restrictive constraint on developers in the urban land development of China.All the plots in Figure 2 are nonparametric plots that use a uniform kernel density regression smoother.

Given that the FAR regulations largely bound the actual FAR decisions of developers, what would be the revenue gain for developers if the city government removes those constraints? Such revenue gains may reflect the regulatory burden by FAR constraints. For each land parcel from the generally matched sample, we calculate the revenue gain based on the following formula:

$$(\hat{F}_i^{AR} - F_{Ri}) \times \text{lot size}_i \times \text{average RDP price within the 1.5 km ring}_i$$

We then take average of this revenue gain by land parcel for each city. We find a significant difference in the revenue gain per land parcel across cities. Shanghai has the highest average revenue gain per land parcel, which is about 1,304 million yuan, followed by Beijing and Hangzhou, at 695 million yuan and 659 million yuan, respectively. This average revenue gain drops dramatically to about 161 million yuan for Chengdu, 88 million yuan for Wuhan, and 81 million yuan for Xi'an. Overall, the average revenue gain per land is much higher in coastal cities than in inland cities. Moreover, within the city, the revenue gain also varies greatly by location. For example, in Beijing, the average revenue gain per land inside the 10-km ring around the city center is about 1,139 million yuan, and declines to 1,058 million yuan between the 10-km and 20-km rings, and further drops to 438 million yuan outside the 20-km ring. Therefore, the FAR regulations may have generated greater distortions of housing supply relative to demand in Chinese cities located in the east than those in the center and west, and within a city, in localities with more valuable attributes than those without.

Although imposing low FAR limits on new land developments in a valuable but already crowded neighborhood may help correct the negative externalities from dense developments (Fu, Gu, and Zhang, 2014), how much restriction is not too much remains a big policy issue. This issue becomes especially relevant in China considering that each residential development project is a lot bigger in size than in other countries, which implies that in making their FAR decisions, developers have probably already internalized the externality of extra floor areas within the same RDP. Understanding how the city government decides the regulatory FAR limits, therefore, carries important policy implications. Besides realizing the market value of precious urban land, several factors can be important for authorities in setting the regulatory FAR limits. For example, in order to protect historical, cultural, and political sites, Beijing and Hangzhou set regulatory FAR limits lower than many other cities. Because of the concern for sinking land ground, Shanghai imposes a lower level of FAR limits in the city center. We leave a full analysis on this topic to the future research.

7. Conclusion

Using a unique data set of residential land matched with the nearby residential development projects, this paper investigates compliance of FAR regulations in urban China. We find that attractive land location attributes tend to induce an upward adjustment of FAR. Moreover, developers who are more likely to have special relationships with government officials are more likely to put more extra floor area above the regulatory FAR limit. We also present evidence that regulatory FAR limits in urban China are much lower than FAR levels maximizing land value, especially for land parcels in relatively more attractive locations. Thus, FAR regulations have imposed a really restrictive constraint on the development of urban land in China.

How should FAR regulations be structured in a developing country like China with relatively weak institutions? Glaeser (2011) suggests an alternative approachfor city planners, where they replace quantity restrictions with a transparent system of fees. In this system, developers are free to choose the FARs of their buildings, while city planners are responsible to form a reasonable estimate of costs created by those tall or dense buildings and charge the developers appropriately. Still, how to enforce such a fee system is challenging and remains open to further study.

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Table 1: Summary statistics

	East Region								Center and West Regions		
	Shanghai	Beijing	Tianjin	Hangzhou	Nanjing	Dalian	Qingdao	Wuxi	Chengdu	Wuhan	Xi'an
Panel A: city level characteristics											
Actual pop 2000 (mm)	16.74	13.57	10.01	6.88	6.23	5.89	7.49	5.18	11.24	8.05	7.41
Actual pop 2010 (mm)	23.02	19.61	12.94	8.7	8	6.69	8.72	6.37	14.05	9.79	8.47
Annu. Pop gwth 00-10 (%)	3.24	3.75	2.60	2.38	2.52	1.28	1.50	2.09	2.25	1.97	1.34
Panel B: residential land parcel characteristics, full sample											
Regulatory FARs	1.65	2.12	1.87	2.28	1.78	2.16	1.92	2.03	3.32	3.00	3.79
	[2.33]	[2.92]	[2.86]	[3.00]	[2.60]	[3.48]	[3.20]	[3.00]	[5.00]	[4.80]	[6.36]
	(0.62)	(0.85)	(0.87)	(0.72)	(0.69)	(1.11)	(1.05)	(0.79)	(1.36)	(1.29)	(1.63)
Distance to city center (km)	24.99	27.22	33.53	14.39	25.79	37.85	29.11	14.37	19.68	16.89	10.38
	(12.96)	(16.78)	(20.55)	(7.98)	(9.11)	(34.52)	(23.44)	(13.78)	(13.29)	(11.78)	(7.79)
Observations	444	430	636	477	393	566	413	378	447	603	309
Panel C: matched sample (1500 m buffer)											
Regulatory FARs	1.683	2.158	2.004	2.318	1.855	2.219	2.160	2.135	3.445	3.212	3.903
	[2.500]	[2.942]	[3.200]	[3.000]	[2.800]	[3.700]	[3.787]	[3.000]	[5.070]	[4.999]	[6.434]
	(0.701)	(0.865)	(0.989)	(0.723)	(0.734)	(1.224)	(1.157)	(0.801)	(1.324)	(1.290)	(1.645)
Distance to city center (km)	22.973	26.605	32.144	13.297	25.735	23.648	20.092	9.997	18.098	14.642	8.768
	(13.109)	(16.432)	(20.466)	(7.269)	(9.075)	(22.769)	(17.680)	(8.834)	(12.787)	(10.700)	(5.309)
Observations	278	355	409	408	295	371	278	299	392	480	278

*Notes:*Standard deviations are in parentheses. 90 percentiles are in brackets.

Table 1: Summary statistics (cont'd)

Panel D: matched RDP's	Mean	Standard deviation	Observations
Average price per floor area (RMB yuan)	11,790	11,289	4,726
Actual FAR	2.724	1.463	4,726
Green space ratio	0.369	0.088	4,681
Dummy: decorated units in RDP	0.298	0.457	4,726
Distance to city center (km)	18.797	24.169	4,726
Distance to nearest subway stop (km)	10.471	58.519	1,520

Table 2: Estimation for the hedonic equation of RDP prices

Dependent variable: log (RDP price)			
	1	2	3
Independent variables			
Log(FAR)	0.140***	-0.001	-0.066***
	(0.011)	(0.010)	(0.014)
Green space ratio	0.281***	0.246***	0.010
	(0.048)	(0.044)	(0.050)
Dummy: decorated units in RDP	0.247***	0.203***	0.124***
	(0.008)	(0.007)	(0.007)
Log(distance to city center)		-0.263***	
		(0.007)	
Log(distance to nearest subway stop)		-0.127***	
		(0.007)	
Ring fixed effects	N	N	Y
City fixed effects	Y	Y	N
R squared	0.439	0.581	0.812
Observations	21,749	21,749	21,749

*Notes:**significance at 10%; **significance at 5%; ***significance at 1%. Heteroskedasticity-robust standard errors are in parentheses, and they are clustered by the 1.5-km ring around the land. Observations are land-RDP pairs.

Table 3: Location attractiveness of landand observedlocation attributes

Dependent variable: the location attractiveness of land			
Independent variables	1	2	3
Log(distance to city center)	-0.537***	-0.510***	-0.507***
	(0.012)	(0.014)	(0.035)
Log(distance to nearest subway stop)	-0.247***	-0.234***	-0.352***
	(0.015)	(0.016)	(0.036)
Log(land reserve price)		0.066***	
		(0.007)	
city fixed effects	Y	Y	Y
R squared	0.648	0.655	0.653
Observations	6,035	4,384	854

*Notes:**significance at 10%; **significance at 5%; ***significance at 1%. Heteroskedasticity-robust standard errors are in parentheses. Column 1 uses all land in the generally matched sample. Column 2 uses the subsample of the land from column 1 whichhasinformation on land reserve prices. Column 3 uses all landin the exactly matched sample.

Table 4: Supporting evidence to the corruption indicator

Dependent variable: Dummy:noncompetitive sale				
	1	2	3	4
	LPM	LPM	Probit	Probit
Dummy: one quarter leads party secretary turnover	-0.074***	-0.075***	-0.250***	-0.251***
	(0.025)	(0.025)	(0.088)	(0.090)
Dummy: one quarter leads party secretary turnover*Location attractiveness		-0.046*		-0.146
		(0.026)		(0.104)
Location attractiveness	-0.031***	-0.028***	-0.103***	-0.095***
	(0.009)	(0.009)	(0.030)	(0.030)
Land characteristics	Y	Y	Y	Y
Season, year, city dummies	Y	Y	Y	Y
observations	4,267	4,267	4,267	4,267

Notes: *significance at 10%; **significance at 5%; ***significance at 1%. Standard errors in parentheses are calculated on the basis of 2,000 bootstrap replications. Land characteristics include log land area, the dummy indicating if the land was partially designated for affiliated commercial properties, and the dummy indicating if the land was partially designated for affiliated public establishments.

Table 5: FAR decisions of the developer

	1	2	3	4	5	6	7	8
	$\bar{F}_0$	$\bar{F}_1$	$\bar{F}_0$	$\bar{F}_1$	$\bar{F}_0$	$\bar{F}_1$	$\bar{F}_0$	$\bar{F}_1$
Location attractiveness α	0.110**	0.032	0.110**	0.032	0.155***	0.107	0.144***	0.100
	(0.045)	(0.092)	(0.046)	(0.094)	(0.044)	(0.093)	(0.046)	(0.097)
Corruption indicator R		0.624**	0.012	0.631*		0.668**	0.153	0.756**
		(0.308)	(0.159)	(0.328)		(0.312)	(0.173)	(0.318)
σ_0	0.723***		0.723***		0.689***		0.688***	
	(0.057)		(0.055)		(0.054)		(0.053)	
σ_1	1.366***		1.366***		1.328***		1.326***	
	(0.130)		(0.130)		(0.120)		(0.123)	
Land characteristics	Y		Y		Y		Y	
Season dummies, linear year trend	Y		Y		Y		Y	
City natural amenities	N		N		Y		Y	
Observations	648		648		648		648	

*Notes:**significance at 10%; **significance at 5%; ***significance at 1%. Standard errors shown in parentheses are calculated on the basis of 2,000 bootstrap replications. Corruption indicator R is the multiplication between the dummy that indicates if the land was sold via a noncompetitive saleand the dummy that indicatesthat the land lies at or above the top 20 percentile in the distribution of location attractiveness.

Table 6: Robustness checks using alternative corruption indicators

	1	2	3	4	5	6	7	8
	$\overline{F}_0$	$\overline{F}_1$	$\overline{F}_0$	$\overline{F}_1$	$\overline{F}_0$	$\overline{F}_1$	$\overline{F}_0$	$\overline{F}_1$
Location attractiveness α	0.153***	0.112	0.155***	0.107	0.155***	0.139	0.154***	0.136
	(0.045)	(0.096)	(0.044)	(0.093)	(0.045)	(0.093)	(0.042)	(0.093)
Corruption indicators R								
Dummy: noncompetitive sale*Dummy: Top10 percentile		0.921*						
		(0.516)						
Dummy: noncompetitive sale*Dummy: Top20 percentile				0.668**				
				(0.312)				
Dummy: noncompetitive sale*Dummy: Top30 percentile						0.247		
						(0.244)		
Predicted probability: two-stage auction								0.870**
								(0.430)
σ_0	0.670***		0.689***		0.689***		0.689***	
	(0.056)		(0.054)		(0.054)		(0.054)	
σ_1	1.328***		1.328***		1.335***		1.329***	
	(0.126)		(0.120)		(0.119)		(0.124)	
Observations	648		648		648		648	

Notes: *significance at 10%; **significance at 5%; ***significance at 1%. Standard errors shown in parentheses are calculated on the basis of 2,000 bootstrap replications. All regressions control for the land characteristics, season fixed effects, a linear year trend, and city-level natural amenities.

Figure 1: Regulatory FAR limits and actual FARs

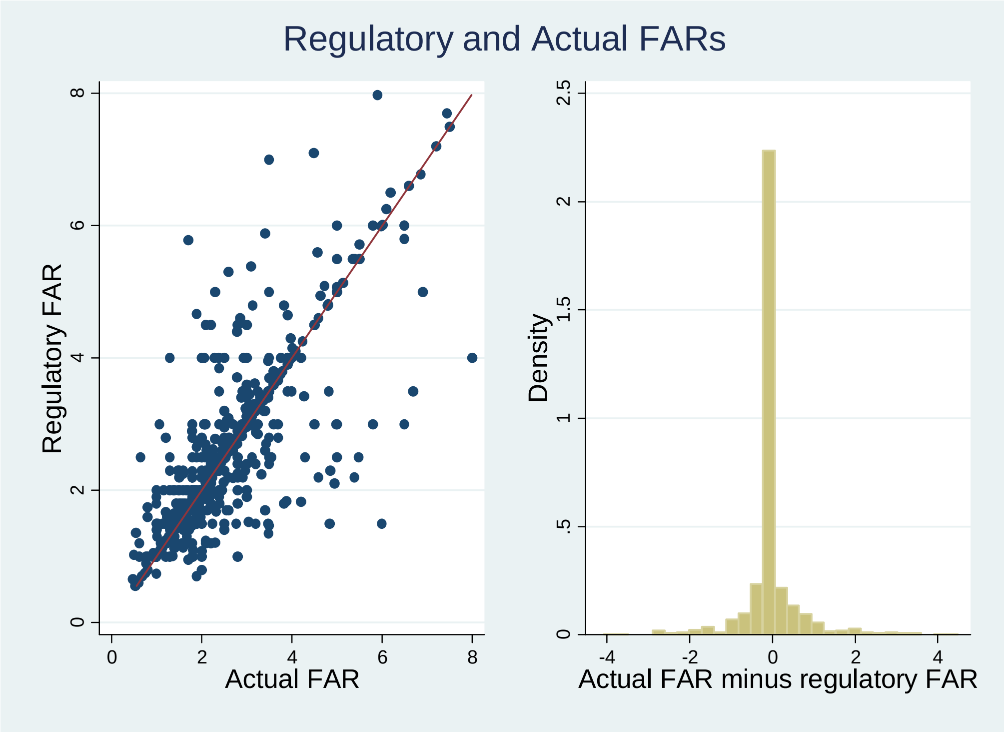
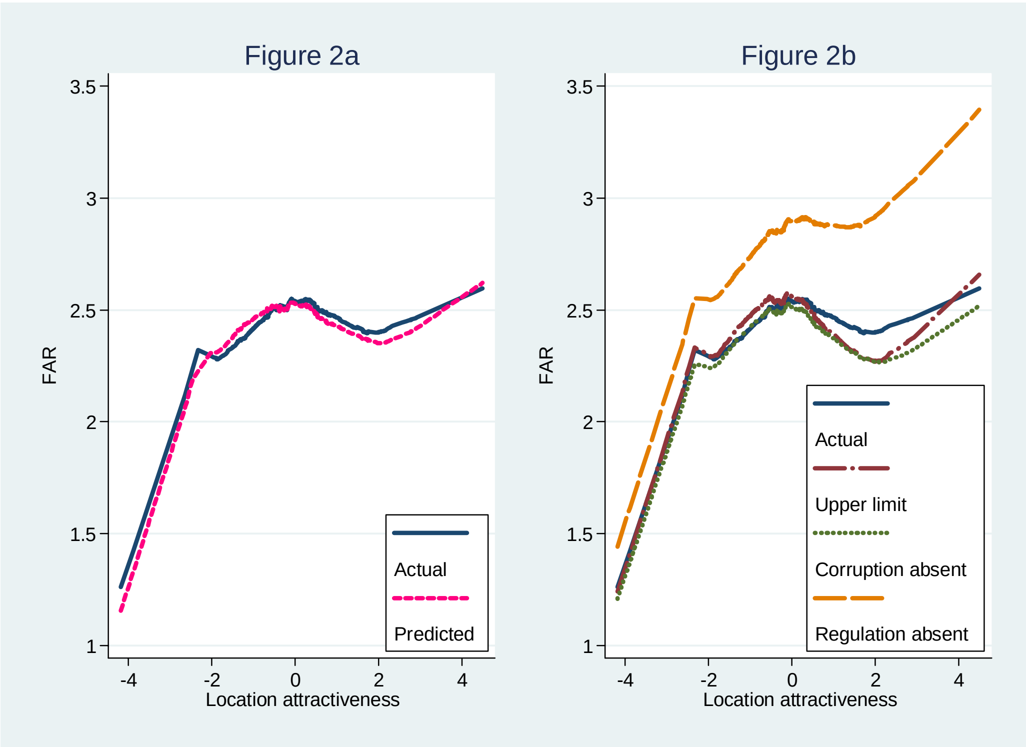


Figure 2: Actual and predicted FARs by location attractiveness



Appendix

For estimation purpose, we define y_i as the difference between F_i and F_{Ri}, i.e., $y_i \equiv F_i - F_{Ri}$. The econometric specification for estimation is given by

$$\text{(A1)}\quad y_i = \begin{cases} \eta_{00} + \eta_0\alpha_i - F_{Ri} + u_{0i} & \text{if} \quad u_{0i} \le -\eta_{00} - \eta_0\alpha_i + F_{Ri} \\ 0 & \text{if} \quad u_{1i} \le -A_1 - \eta_1\alpha_i - \lambda R_i + F_{Ri},\ u_{0i} > -\eta_{00} - \eta_0\alpha_i + F_{Ri} \\ A_1 + \eta_1\alpha_i + \lambda R_i - F_{Ri} + u_{1i} & \text{if} \quad u_{1i} > -A_1 - \eta_1\alpha_i - \lambda R_i + F_{Ri} \end{cases}$$

Simply the notations byletting $z_i \equiv (1, \alpha_i, F_{Ri})$,we then rewrite (A1) as follows:

$$\text{(A2)}\ y_i = \begin{cases} z_i\gamma_0 + u_{0i} & \text{if} \quad u_{0i} \le -z_i\gamma_0 \\ 0 & \text{if} \quad u_{1i} < -z_i\gamma_1,\ u_{0i} > -z_i\gamma_0 \\ z_i\gamma_1 + u_{1i} & \text{if} \quad u_{1i} \ge -z_i\gamma_1 \end{cases}.$$

If (z_i, y_i) is a random draw from the population, the density of y_i given z_i is

$$\frac{1}{\sigma_1}\phi\left(\frac{y_i - z_i\gamma_1}{\sigma_1}\right), \text{ if } y_i > 0$$

$$P(y_i = 0 \mid z_i) = \Phi\left(\frac{-z_i\gamma_1}{\sigma_1}\right) - \int_{-\infty}^{(-z_i\gamma_1)/\sigma_1}\int_{-\infty}^{-z_i\gamma_0/\sigma_0} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\{-\frac{1}{2(1-\rho^2)}(s^2 + t^2 - 2\rho st)\}dsdt\ ,$$

$$\frac{1}{\sigma_0}\phi\left(\frac{y_i - z_i\gamma_0}{\sigma_0}\right)\Phi\left(\frac{-z_i\gamma_1 - \rho\sigma_1\left(\frac{y_i - z_i\gamma_0}{\sigma_0}\right)}{\sqrt{1-\rho^2}\,\sigma_1}\right), \text{ if } y_i < 0$$

, where ϕ and Φ are the PDF and CDF of the standard normal distribution, respectively. Using the density functions shown above, we can obtain the log-likelihood function for each observation, based on which the maximum likelihood estimation is run.