Measuring the Stringency of Land-Use Regulation and Its Determinants: The Case of China's Building-Height Limits

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Abstract

During the rapid urbanization of recent years, local governments in China have increasingly relied on land leases to independent developers as a source of revenue. The long-term land leaseholds always contain floor-area-ratio (FAR) restrictions, which specify the maximum allowed ratio of a building's total floor area to its lot size, effectively limiting building height. In this study, we seek to understand how FAR restrictions affect urban land prices and how such restrictions vary across locations and over time. Our model implies that relaxation of an FAR restriction increases the land price, and that the elasticity of price with respect to FAR is an indicator of the stringency of the restriction. We use two unique data sets to perform empirical analysis: one contains information on land transactions in more than 200 Chinese cities during 2002-2011, and the other covers developed land parcels in Beijing whose FARs were adjusted over the 1999-2006 period in response to changes in local conditions. We find that higher allowed FARs lead to higher land prices, that this effect varies significantly both across cities and across locations within a city (indicating variation in the stringency of the limits), and that positive demand shocks led to upward adjustment of FARs in Beijing.

Keywords: Floor area ratio, density restriction, urban development, China.

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1 Introduction

Land-use regulation has been a long-time focus of research by economists and other scholars. Regulations are imposed in virtually every country in the world and take a variety of forms. They include traditional zoning laws, which are designed to allocate land to different uses while spatially separating them; restrictions on the density of development, which range from building-height limits to minimum lot-size requirements to street set-back rules; and restrictions on the volume of development, which include urban growth boundaries that limit the land area available for development and annual caps on building permits. Empirical research on land-use regulation has mainly focused on its impact on the prices of both housing and land, although a few studies measure its effect on the rate of new construction (see Gyourko and Molloy (2014) for an up-to-date survey). The evidence shows that regulations tend to raise housing prices, a consequence of their tendency to restrict housing supply, an effect that is separately documented in other studies.

The fact that regulations have price effects indicates that they are binding on development decisions. While this is an important finding, the literature to date contains few attempts to measure the *stringency* of land-use regulations, namely, the *extent to which they cause development decisions to diverge from free-market outcomes.* For example, highly stringent density restrictions would reduce development density far below the unregulated level, while less-stringent regulations would have a milder effect.[1] A highly stringent urban growth boundary would constrain a city's footprint to be much smaller than its free-market size, while a less-stringent one would leave the footprint almost unaffected. Stringent zoning regulations could seriously skew a city's division of land between residential and commercial uses away from a free-market division.

A major purpose of this paper is to provide a rare inquiry into the stringency of land-use regulation, using a theoretical model to guide empirical work based on an extraordinary data set of land-lease transactions in China. We focus on the regulated floor-area ratio (FAR) for the leased parcel, which limits the ratio of the floor area within the proposed building to the parcel's lot size. Although FAR is affected by the amount of open space left on the lot, it is effectively a measure of the allowed building height. A stringent FAR limit will thus constrain the building height to be much lower than the one the developer would choose in the absence of regulation. The unconstrained FAR is, of course, unobservable in the presence of the regulation, which means that the stringency of FAR limit cannot be gauged directly. However, we demonstrate theoretically that the stringency of the limit can be inferred from the connection between land prices for leased parcels (which are available in the data) and their FAR limits, and we then use this connection to evaluate the stringency

[1] One line of work that provides a measure of regulatory stringency was originated by Glaeser et al. (2005). They compare the marginal value of floor space estimated from an hedonic model to construction cost per square foot for residential buildings in Manhattan, with the gap being an index of the extent to which height regulations restrict development density below market levels. Further references can be found in Gyourko and Molloy (2014).

of *FAR* regulation in Chinese cities.

Because *FAR* regulation reduces the profitability of development, it reduces the developer's willingness-to-pay for the land and thus its value. Accordingly, a higher allowed *FAR*, by loosening the constraint on development, will raise the land price for the parcel. But theory shows that a more-precise conclusion can be derived. We show that the elasticity of land price with respect to the *FAR* limit depends on the *ratio of the unconstrained and regulated FAR levels*. In particular, this elasticity is large when that ratio is large, or when the unconstrained *FAR* is high relative to the regulated *FAR*. Thus, relaxing a highly stringent *FAR* limit (one with a high ratio) leads to a greater percentage increase in land price than relaxing a less-stringent limit, an intuitively sensible conclusion.

We exploit this result using the land-lease data, which consists of 120,000 transactions across more than 200 cities over the 2002-2011 period, to gauge the restrictiveness of *FAR* regulation in China, while also exploring additional questions. Under our first approach, we view *FAR* restrictiveness as being city-specific, running a land-value regression using lease transactions from all cities but allowing each city to have a different elasticity of individual parcel values with respect to parcel-specific *FAR* limits. The estimated elasticity coefficients then tell us which Chinese cities are most restrictive in their regulation of *FAR*. Under the second approach, we focus on a single large city (Beijing), allowing the land-price/*FAR* elasticity (and thus *FAR* restrictiveness) to vary according to site characteristics such as distance from the historic city center. We also investigate the city-level determinants of *FAR* values using the full national data set, showing which city characteristics lead to tight building-height limits. A companion regression relates the *restrictiveness* of *FAR* at the city level (as captured by city-specific coefficients in the land-price regression) to city characteristics. Using a different data set for Beijing that shows *FAR* limits for existing properties rather than new transactions, we explore the factors that cause regulated *FAR* levels to change over time.

Despite the importance of *FAR* restrictions in guiding Chinese urbanization, only three rigorous studies (to the best of our knowledge) have previously investigated these restrictions. Fu and Somerville (2001) develop a theoretical model and then show empirically that restricted *FAR* values deviate from the developer's optimal value in a way that reflects the local government's goals. In an unpublished study, Gu and Zheng (2009) use a unique data set that contains information on revisions of land-use plans to show that city planners respond to changes in market conditions when adjusting *FAR* restrictions. In a more recent paper, Cai, Wang, and Zhang (2014) investigate violations of *FAR* restrictions in China, which are subject to a penalty. Using a unique data set, they find that land developers tend to violate *FAR* restrictions in more desirable locations, that higher penalties deter violations, and that corruption boosts violations.[2]

[2] A few related studies examine *FAR* regulation in other countries. Using data on 273 land lots in the Tokyo area, Gao et al. (2006) estimate hedonic regressions to explore the effect of *FAR* restrictions on land prices. In contrast to this study, they treat the *FAR* restriction as an exogenously determined lot attribute.

The plan of the paper is as follows. Section 2 provides an overview of the institutional setting in which land-lease transactions occur. Section 3 presents the theoretical model. Section 4 describes the national data set and presents the results of the intercity regressions. Section 5 presents the regression results using the Beijing portion of the national data and then presents regressions using the separate Beijing data set on *FAR* values for existing properties. Section 6 offers conclusions.

2 Institutional Background

China is experiencing rapid urbanization, with the share of the urbanized population rising from 21 percent in 1982 to over 50 percent today. This fast urban population growth has been accommodated by an unprecedented spatial expansion of the country's urbanized areas. In 1982, China's built-up urbanized area was 7,438 square kilometers. By 2011, it had risen to 43,603 square kilometers.[3]

This explosive urbanization was fueled by rapid conversion of land from rural to urban use, a process facilitated by local governments. By Chinese law, urban land is owned by the state, and rural land is owned by local economic collectives. To facilitate urban expansion, local governments acquire land from farmers at the urban fringe, paying compensation that is often substantially below market value (Ding 2007, Hui et al. 2013). The local governments then transfer land-use rights to independent developers via a leasehold, generating revenue that can be used for public investment and other purposes.[4] In earlier years, lease payments were decided through negotiations between land developers and government officials, which were conducive to corruption. Since 2004, local governments have used land auctions to make the transactions of land-use rights more transparent.[5] The maximum term of the land lease is 70 years for residential uses, 50 years for industrial uses, and 40 years for commercial uses.[6]

A local government's land-use plan stipulates how a developer can use the leased land.[7]

Brueckner and Sridhar (2012) measure welfare gains from relaxation of *FAR* restrictions in India. Barr and Cohen (2014) describe the *FAR* gradient and its evolution in New York City.

[3]See Ministry of Housing and Urban-Rural Development (2012) and National Bureau of Statistics of China (1983, 2012).

[4]Fiscal decentralization, a key component of China's economic reform, was accomplished in the early 1980s through a "fiscal contract system," under which local governments could keep all (or almost all) extra revenues they generated beyond their pre-set contract responsibilities. This system created an environment in which local governments and their officials benefited greatly from local economic prosperity, giving local officials a significant incentive to pursue economic and revenue growth. Following a major tax reform in 1994, which weakened the tax base for local governments, local government officials learned that selling land-use rights is an effective way to generate revenue. "Land finance" has since become a key feature of local public finance in China (Cao et al. 2008). In recent years, around 50 percent of local government revenue comes from land-use right transfers (Liu et al. 2012).

[5]Cai et al. (2014) present a variety of indirect evidence to show that corruption also exists in land auctions.

[6]When different branches of the government need land for construction of public infrastructure or military facilities, land-use rights can be obtained through a direct allocation.

[7]Prior to the economic reform, urban planning in China was essentially an extension of the macroeconomic

The plan usually specifies the usage type, indicating whether the land is for residential, commercial, or industrial development, and it contains density restrictions, including the FAR, green coverage, and sometimes a separate explicit height limit. In other countries such as the United States, land-use regulations also restrict development density, but these restrictions typically apply to many land parcels in a large section of a city. The unique characteristic of urban planning in China is that controls and restrictions are designed and implemented at the land parcel level. For our study, this unique institutional arrangement allows us to study FAR restrictions at the land parcel level, both theoretically and empirically. As will be seen shortly, a local government interested in maximizing revenue from land leases would impose *no land-use restrictions at all*, recognizing that unrestricted profit-maximization on the part of developers leads to the highest land price. FAR restrictions will be desirable, however, once it is recognized that the high densities associated with high $FARs$ impose costs on the local government, including the cost of providing supporting infrastructure to the newly built community. As a result, local officials will not allow developers to set an unrestricted, profit-maximizing FAR, which would maximize land revenue, but will instead sacrifice revenue by restricting the allowable FAR, with the goal of limiting the infrastructure costs associated with higher densities.[8] In this sense, local officials behave as *net revenue* maximizers, taking the public costs associated with land development into account.[9] The resulting restrictions then generate an association between land price for a site and its FAR limit, and by studying the strength of this association, we can infer the restrictiveness of the limit.

plan, which was concerned with the spatial distribution of industrial plants and the physical structure of urban centers. After the inception of the market-oriented reform, urban planning in China was transformed to deal more with micro issues related to urban development. Land-use permitting, management, and regulation have since become major functions of urban planning.

[8]It is a well-known theoretical point that FAR and other housing density restrictions can be explained by invoking population-density externalities. See, for example, Bertaud and Brueckner (2005), Joshi and Kono (2009), Kono and Joshi (2012), Kono et al. (2010), Mills (2005), Pines and Kono (2012), and Wheaton (1998).

[9]Lichtenberg and Ding (2009) have similarly treated local government officials in China as rational decision makers in the context of land conversion for urban uses, and Zhang (2011) assumes local government officials to be rational revenue maximizers in a study of inter-jurisdictional competition for FDI in China. Local government officials indeed have multiple reasons to boost government revenues from land transfers. First, a large amount of revenue makes it much easier for local government officials to do their job, such as providing local public education and improving local infrastructure. Second, a great amount of land revenue indicates a prosperous local economy, which helps government officials climb up the hierarchy within the ruling party's cadre system (Liu et al. 2012). In China, government officials are not elected through a democratic system; they are promoted by upper level officials in the communist party. At least during the post-reform era, economic performance of their jurisdictions has been an important factor that determines the career paths of local government officials. As shown by Li and Zhou (2005) and follow-up research, better economic performance increases a local leader's probability of being promoted and decreases the probability of his or her career termination. Third, a steady stream of land revenue also rewards government officials financially. Part of the revenue will become perks and fringe benefits for them; part of it will be used to fund their work-related travel and consumption; and of course, part of it may end up in the officials' pockets through corruption, fraud, or other questionable conduct.

3 Model

3.1 Measuring *FAR* stringency

To explore the connection between land price and FAR, consider the standard urban land-use model, as in Brueckner (1987). While this model is static, ignoring the long-lived nature of housing, the following analysis can be adapted easily to the case where a housing investment earns revenue over an extended period. Let r denote the land price per acre and p denote the price per square foot of housing, which depends on a vector Z of locational attributes, including distance to the CBD, that affect the attractiveness of the site (thus, $p = p(Z)$). Let $h(S)$ denote square feet of housing output per acre as a function of structural density S, which equals housing capital per acre (h is concave, satisfying $h' > 0$ and $h'' < 0$). The housing developer's profit per acre is given by

$$\pi = ph(S) - iS - r, \tag{1}$$

where i is the cost per unit of capital. The first-order condition for choice of S in the absence of an FAR limit is

$$ph'(S) = i, \tag{2}$$

and the S satisfying (2) is denoted S^*. The land price is then given by the zero profit condition:

$$r = ph(S^*) - iS^*. \tag{3}$$

An FAR limit imposes a maximal value for $h(S)$, denoted $\overline{h}$, which in turn imposes a maximal value of S. This value is denoted $\overline{S}$, and it satisfies $h(\overline{S}) = \overline{h}$. The effect of $\overline{S}$ on the land price r is considered first, with the link between r and $\overline{h}$ analyzed below. Faced with the FAR limit, developers will set $S = \overline{S}$, and the land price will be given by

$$r = ph(\overline{S}) - i\overline{S}. \tag{4}$$

The derivative of land price with respect to $\overline{S}$ is

$$\frac{\partial r}{\partial \overline{S}} = ph'(\overline{S}) - i > 0, \tag{5}$$

where the inequality follows because the FAR constraint is binding, with S restricted below its optimal value. If the FAR limit is not binding, then it will have no effect on development decisions and thus no effect on r. In addition, the land price will depend on the vector Z:

$$\frac{\partial r}{\partial Z} = \frac{\partial p}{\partial Z} h(\overline{S}). \tag{6}$$

A higher value of a favorable site characteristic j such as accessibility to employment, for which $\partial p / \partial Z_j > 0$, will raise the land price.

Consider the elasticity of land price with respect to $\overline{S}$, which is given by

$$E_{r,\overline{S}} \;\equiv\; \frac{\partial r}{\partial \overline{S}}\frac{\overline{S}}{r} \;=\; \frac{[ph'(\overline{S}) - i]\overline{S}}{ph(\overline{S}) - i\overline{S}}. \tag{7}$$

Since concavity of h means that $h'(\overline{S})\overline{S} < h(\overline{S})$, $E_{r,\overline{S}}$ in (7) is less than unity, so that the elasticity of land value with respect to a binding S limit is less than one.

To get additional information, $ph'(S^*) = i$ can be used to eliminate i in (7). Doing so, the expression becomes

$$E_{r,\overline{S}} \;=\; \frac{\left[ph'\left(\overline{S}\right) - ph'\left(S^*\right)\right]\overline{S}}{ph\left(\overline{S}\right) - ph'\left(S^*\right)\overline{S}} = \frac{\left[h'\left(\overline{S}\right) - h'\left(S^*\right)\right]\overline{S}}{h\left(\overline{S}\right) - h'\left(S^*\right)\overline{S}}, \tag{8}$$

showing that $E_{r,\overline{S}}$ depends on S^* as well as $\overline{S}$ (note that p cancels). At this point, it is useful to impose a standard functional form for h. If $h(S) = S^\beta$, with $\beta < 1$, then (8) becomes

$$E_{r,\overline{S}} \;=\; \frac{\left[\beta\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}\right]\overline{S}}{\overline{S}^{\beta} - \beta\left(S^*\right)^{\beta-1}\overline{S}} \;=\; \frac{\beta\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}}{\overline{S}^{\beta-1} - \beta\left(S^*\right)^{\beta-1}} \;=\; \frac{(S^*/\overline{S})^{1-\beta} - 1}{\frac{1}{\beta}(S^*/\overline{S})^{1-\beta} - 1}. \tag{9}$$

Thus, the elasticity of land price with respect to $\overline{S}$ depends on the ratio of the developer's optimal S (S^*) to the restricted level, $\overline{S}$. Furthermore, differentiation of (9) shows that

$$\frac{\partial E_{r,\overline{S}}}{\partial(S^*/\overline{S})} \;>\; 0, \tag{10}$$

so that the elasticity is large when the restricted S lies far below the optimal value (making $S^*/\overline{S}$ large). In other words, the percentage increase in land price from relaxing a very tight $\overline{S}$ limit is greater than the percentage increase from relaxing a looser limit, a conclusion that matches intuition.

Since $h(\overline{S}) = \overline{h}$ implies $\overline{S}^\beta = \overline{h}$ under the chosen functional form, it follows that $\overline{S} = \overline{h}^{1/\beta}$. Therefore, the elasticity of land price with respect to $\overline{h}$, denoted $E_{r,\overline{h}}$, equals $1/\beta$ times the elasticity with respect to $\overline{S}$, so that

$$E_{r,\overline{h}} \;\equiv\; \frac{\partial r}{\partial \overline{h}}\frac{\overline{h}}{r} \;=\; \frac{E_{r,\overline{S}}}{\beta}. \tag{11}$$

Given (11), it follows that $E_{r,\overline{h}}$, like $E_{r,\overline{S}}$, is increasing in $S^*/\overline{S}$:

$$\frac{\partial E_{r,\overline{h}}}{\partial(S^*/\overline{S})} \;>\; 0. \tag{12}$$

Thus, the percentage increase in land price from relaxing a tight FAR limit is greater than the increase from relaxing a loose one. Note that since both $E_{r,\overline{S}}$ and β are less than 1, the elasticity $E_{r,\overline{h}}$ can be either larger or smaller than 1, in contrast to $E_{r,\overline{S}}$ itself.

3.2 Empirical implementation

The result in (12) can be exploited via estimation of a land price regression relating the log of land price to the log of the FAR limit along with the vector Z. In a single city, the regression would have the form

$$\ln r_i = \alpha + \theta \ln FAR_i + Z_i\gamma + \epsilon_i, \tag{13}$$

where θ is the elasticity of land price with respect to *FAR*, γ is the vector of coefficients on site characteristics, ϵ is the error term, and i denotes individual land parcels. Our first exercise is to estimate this model using the entire national data set, assuming a uniform elasticity θ but allowing intercepts to differ across cities and the administrative districts within them as well as by time (a typical city contains around 5 districts). Under this approach (13) becomes

$$\ln r_{jcdt} = \alpha_{cdt} + \theta \ln FAR_{jcdt} + \epsilon_{jcdt}, \tag{14}$$

where j denotes parcels, c cities, d districts, and t years. City-district-year fixed effects are denoted by α_{cdt}. Note that these fixed effects subsume the Z variable from (13).

A second approach is to allow the elasticity θ to be city-specific, so that (14) becomes

$$\ln r_{jcdt} = \alpha_{cdt} + \theta_c \ln FAR_{jcdt} + \epsilon_{jcdt}. \tag{15}$$

To interpret (15), suppose that some cities are highly restrictive in their *FAR* regulations, with the $\overline{S}$ values for individual parcels far below the optimal S^* values, while the other cities are less restrictive, with $\overline{S}$'s closer to the S^*'s. Then, the estimated θ_c's for the cities in the first group would be larger than the estimated θ_c's for cities in the second group. Therefore, *differences across cities in estimated θ values reflect differences in the restrictiveness of their FAR regulations.*

Alternatively, a variant of the regression in (13) could be used to explore how *FAR* restrictiveness *varies across locations within a single large city*, which has enough parcel observations to carry out a regression. To make such an inference, the impact of *FAR* on land price could be allowed to depend on site characteristics, measurement of which is infeasible in the large national data set but is practicable in a smaller single-city sample. For example, suppose *FAR* restrictiveness depends on distance from the city center, denoted by x, with the relationship between $\overline{S}$ and S^* depending in some fashion on this distance measure (x is one element of Z). This outcome could be captured by dropping the *cd* index and rewriting the regression in (14) as

$$\ln r_{it} = \alpha + \beta_t + \theta \ln FAR_{it} + \eta(x_{it} * \ln FAR_{it}) + Z_i\gamma + \epsilon_i, \tag{16}$$

with FAR now also appearing in an interaction term involving x. If the estimated η is negative, the implication is that FAR restrictiveness is lower farther from the city center, while a positive η would indicate that greater restrictiveness farther from the center.

3.3 Determinants of *FAR*

The analysis so far has taken the FAR limit as given, but there is reason to believe that government officials pursue their own goals when setting FAR limits, potentially making FAR endogenous. Consider a local government official's decision to choose the FAR for a land parcel. Like the developer, the official understands the determination of land prices and also recognizes that the development generates some extra public infrastructure costs for the local government in the amount of $K(S)$ (for roads, sewers, water lines, etc). $K'(S) > 0$ holds because denser development requires more and/or better supporting infrastructure. We assume that the local government official seeks to maximize the net revenue from land development:

$$r - K(S) = ph(S) - iS - K(S). \tag{17}$$

Thus, the government official's optimal structural density $\overline{S}$ satisfies the condition

$$ph'(\overline{S}) - K'(\overline{S}) = i. \tag{18}$$

Recall that, at the developer's optimal density S^*, $ph'(S^*) = i$. Given that $h' > 0$, $h'' < 0$, and $K' > 0$, it follows that $\overline{S} < S^*$. As a result, the government-imposed FAR, $\overline{h} = h(\overline{S})$, is below $h(S^*)$, and it will thus be binding.[10]

Equation (18) implies that the variables Z affecting the housing price p (e.g., local amenities) will in turn influence the FAR limit chosen by the government, and that any variables V affecting the government's marginal infrastructure cost (K') will also affect the FAR limit. Therefore

$$\overline{h} = \overline{h}(Z, V). \tag{19}$$

From equations (4) and (19), we know that, if any unobserved site attributes are correlated with the local housing price, they will also be correlated with both land price and the FAR limit. Thus, the coefficients from OLS estimation of (14), (15), and (16) are likely to be biased due to omitted variables. To solve this problem, we would ideally use one or more instrumental variables for FAR, variables that appear in V in (19) but are not included

[10] As a result, the developer has an incentive to bribe government officials to relax the FAR constraint, which indeed happens in China. In 2009, an investigation of 73,139 land leases revealed that in 2.72% of them, the planned floor-area ratios were illegally adjusted (http://china.findlaw.cn/fagui/p_1/340505.html). See Cai et al. (2014) for a study that focuses on violations of FAR restrictions.

in Z. Thus, infrastructure cost measures, such as public sector wages or the share of new infrastructure costs paid by the upper-level government, might be candidate instrumental variables for FAR.

4 Intercity Analysis

4.1 Data sources

This section presents results from the intercity analysis, where (14) and (15) are estimated using the national data set. To generate this data set, we use both proprietary and public data sources. The main data come from the China Index Academy (CIA), the largest independent research institute in China focusing on real estate and land issues. CIA aims to provide comprehensive and accurate real estate and land data as well as related market consulting services. One of CIA's major products is its database on land transactions in over 200 cities across China. Our extract of the data was generated in early 2012. It contains information on over 120,000 land transactions during 2002-2011.[11] Our analysis focuses on residential and commercial land; land transactions for other uses (industry, warehouse, public facilities, education, etc.) are dropped. For each land parcel, we know its location, usage type, planned floor area, planned FAR, planned green coverage, planned structural density, the auction start and end days, price per unit of planned floor area, price per unit of land, required deposit for bidders, minimum incremental bid, winner of the auction, selling price, and transaction date.

In some cases, the FAR restriction is specified as a single number. In other cases, it is given as a range, in which case we use the upper limit of the range. To reduce the influence of extreme observations, we dropped the outliers from the top and bottom one percent of land prices and from the top and bottom one percent of maximum allowed FAR.

Table 1 presents some descriptive statistics from the CIA data. The upper panel shows the average maximum allowed FAR by city size. For residential land uses, it is the medium-sized cities that allow the highest floor-area ratios; for commercial land uses, there is a clear pattern that larger cities have higher FARs. The average falls between 2 and 3, lower than dense European cities, which typically have floor area ratios between 3 and 4 (World Bank 2014, p.142). The lower panel shows the average maximum allowed FAR in different time periods. For both residential and commercial land uses, the maximum allowed FAR has tended to become higher over time.[12] Note that during the 2002-2011 decade, housing prices grew increasingly faster in Chinese cities, and city planners might

[11] The data set also contains a small number of land transactions before 2002. CIA's data collection effort focuses primarily on transactions through land auctions. Since land auctions were not commonly used before 2002, their data coverage in those early years appears to be very poor. So we decided to drop such pre-2002 observations from our analysis.

[12] The higher mean FAR for commercial land in 2002-2003 comes from a very small sample, which is not representative because, at that time, some land transactions were not conducted through auction and thus would not be captured by the data.

Table 1: Average maximum allowed floor area ratios

	Land for residential uses		Land for commercial uses	
	By city size			
	Mean FAR	No. of obs.	Mean FAR	No. of Obs.
Population $\geq$ 2 million	2.352	15,024	2.516	12,819
2 million $>$ Pop. $>$ 1 million	2.456	7,820	2.427	6,644
Population $\leq$ 1 million	2.425	6,505	2.316	5,117
	By year of transaction			
	Mean FAR	No. of obs.	Mean FAR	No. of Obs.
2002-2003	1.846	733	2.419	405
2004-2005	2.083	1,920	2.104	1,804
2006-2007	2.298	3,732	2.425	3,253
2008-2009	2.368	6,508	2.488	5,509
2010-2011	2.487	16,906	2.488	13,609

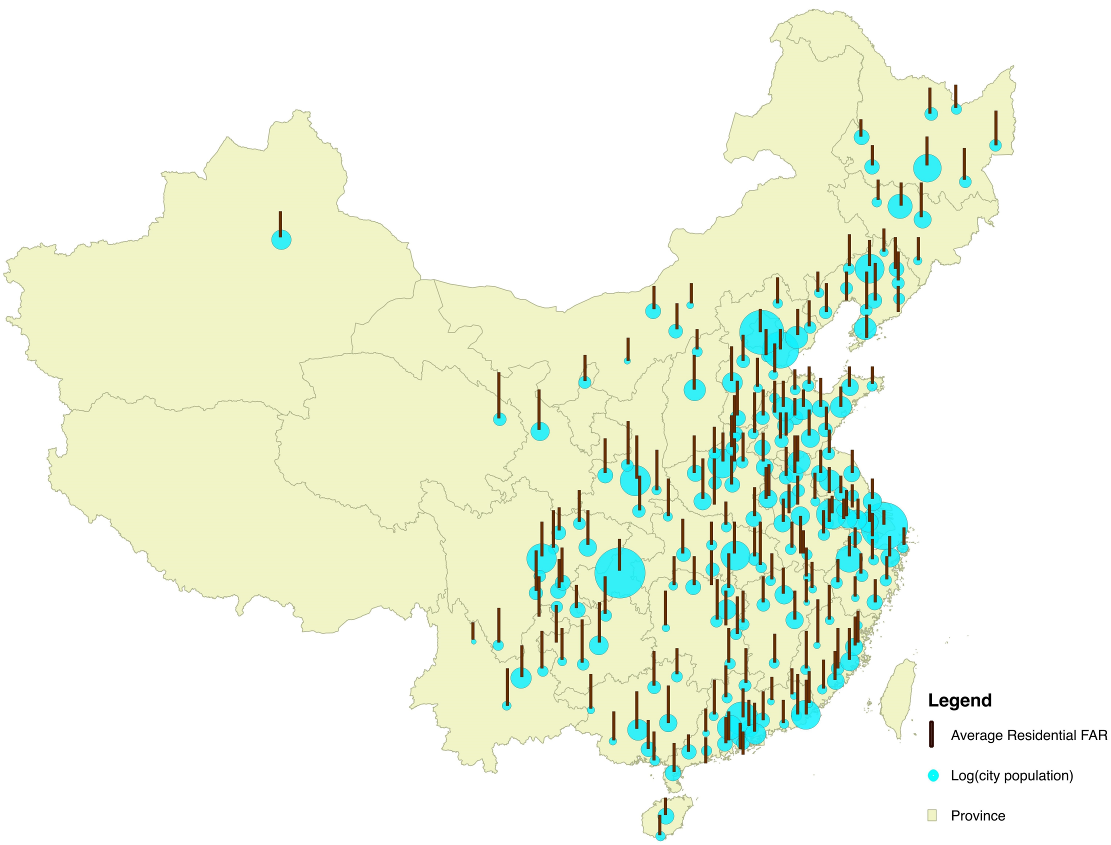
Classification of city size is based on population in 2005.

have adjusted their expectations of housing-price growth rates accordingly. Both higher and faster-growing housing prices would imply higher allowed FARs over time, as implied by equation (18).

Figure 1 shows a map of China indicating cities where the CIA data on land auctions are collected. Each blue circle indicates the size of the city by 2010 population; the height of the bar represents the average FAR for residential land in the city. Cities covered by the data are mostly in the East or central region, and very few are in the West, reflecting the distribution of population and economic activity in the country. From the different heights of the bars, we see that the average FAR varies a great deal across cities. The largest cities, such as Beijing, Shanghai, and Tianjin, have rather low average floor area ratios, which is somewhat surprising. Upon closer examination, it appears that these largest cities tend to have more land transactions during the early years of the sample period, more land transactions at the urban edge far from the city center, and more richer families with higher demand for open space. All of these factors may imply a lower average FAR.

To supplement the CIA data, we collected information on city characteristics from different editions of the *China Urban Statistical Yearbook*, including the following variables: population, fiscal revenue per capita, number of public buses per capita, paved road area per capita. Merging these variables with the CIA land transactions data allows us to explore how FAR restrictions vary with city characteristics, once the land price regressions have been estimated.

Figure 1: Floor area ratio restrictions in Chinese cities



Note: The size of the circle represents the 2010 population of the city; the height of the bar represents average maximum allowed floor area ratios in the city over different years.

4.2 Results

Table 2 presents estimation results for the land-price regressions. Whereas our model was developed in the context of residential land uses, we run the same set of regressions with commercial land transactions for comparison.[13] We first estimate equation (14), where a uniform nationwide θ is assumed, and the results are presented in panel A. Controlling for city-district-year fixed effects, we find that log land price is indeed positively associated with log FAR, indicating that FAR restrictions are binding on average. This finding emerges for both residential and commercial land, although the coefficient for residential land is much larger. Note that the standard errors for the regression are clustered at the city-district level.[14]

Panel B of Table 2 shows the results from estimation of (15), where the θ coefficients are allowed to vary across cities (standard errors are now clustered by city). To improve the precision of estimation, we estimate separate coefficients only for cities with 100 or more land sales in the sample and lump all other cities into one group. For residential land, we estimated 73 city-specific coefficients. The average of these estimates is 0.7481, almost identical to the single coefficient estimated in panel A (0.7466). The coefficients range from -0.0110 to 1.5543, and almost all are positive. For commercial land, we estimated 62 city-specific coefficients. The average is 0.5927, also fairly close to the single estimate in panel A (0.5669). All of the coefficients are positive, ranging from 0.1025 to 1.2307.

In panels (*i*) and (*ii*) of Figure 2, we plot the distributions of city-specific coefficients. For both residential and commercial land, there is a great deal of heterogeneity in the estimated coefficients. Although, for residential land, the average coefficient is 0.75, some cities at the lower end of the distribution have coefficients very close to zero, suggesting that land prices and regulated FAR are hardly correlated in those cities. By contrast, at the upper end of the distribution, some cites have coefficients higher than 1. That is, a 1% increase in regulated FAR is associated with a more than 1% increase in land price. Overall, these results suggest that the stringency of FAR regulations varies a great deal across cities. Whereas the limits are hardly restrictive in some cities (generating θ coefficients close to zero), in other cities they represent a serious constraint on development density, generating large positive coefficients.

It is interesting to observe exactly where different cities lie in the distribution of coefficients. To address this question, we list all the coefficients for the residential regression in the Appendix Table. The list on the left comes from the regression in column (1) of panel B in Table 2. Among the cities with the smallest coefficients, Qinhuangdao, Erdos,

[13] There are many land sales that are planned for "mixed" (both residential and commercial) uses. We include these observations in both the residential and commercial samples.

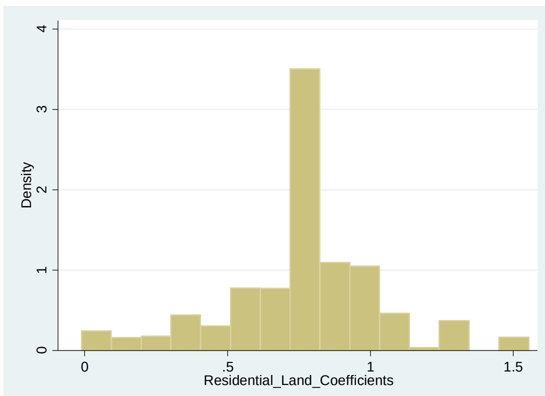
[14] For 36% (10,507 out of 29,349) of the residential land parcels and 37% (9,086 out of 24,580) of the commercial land parcels, a minimum FAR requirement is also specified in the CIA data. We estimate a set of regressions similar to those in panel A, using minimum instead of maximum FAR as the independent variable. The coefficients, 0.589 and 0.500 for residential and commercial land respectively, are also positive and highly significant. These results suggest that the minimum FAR requirement is not binding.

Table 2: Regressions of log land price on log floor area ratio

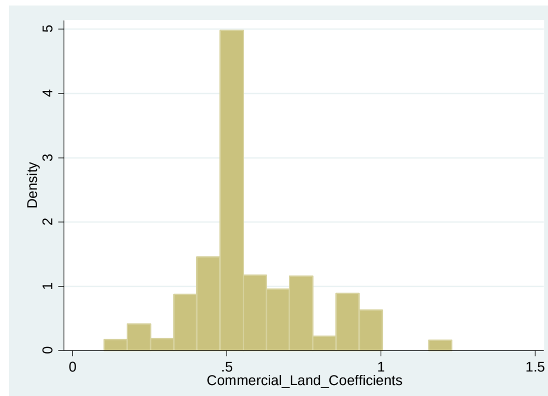
Dependent Variable: Log unit land price		
Variable	(1) Residential Land	(2) Commercial Land
A. Same coefficient in all cities, full sample		
Log floor area ratio	0.7466***	0.5669***
	(0.0303)	(0.0204)
City-district-year fixed effects	Yes	Yes
Adjusted R^2	0.6345	0.5850
Number of observations	29,349	24,580
B. Allow for different coefficients across cities, full sample		
Log floor area ratio	73 city-specific coefficients	62 city-specific coefficients
	Mean: 0.7481	Mean: 0.5927
	Std. Dev.: 0.3250	Std. Dev.: 0.2502
City-district-year fixed effects	Yes	Yes
Adjusted R^2	0.6424	0.5911
Number of observations	29,349	24,580
C. Same coefficient in all cities, matched sample		
Log floor area ratio	0.3572***	0.3641***
	(0.0782)	(0.0649)
Cluster fixed effects	Yes	Yes
Adjusted R^2	0.9431	0.9322
Number of observations	5,675	4,052
D. Allow for different coefficients across cities, matched sample		
Log floor area ratio	38 city-specific coefficients	27 city-specific coefficients
	Mean: 0.2876	Mean: 0.2572
	Std. Dev.: 0.3472	Std. Dev.: 0.4323
Cluster fixed effects	Yes	Yes
Adjusted R^2	0.9455	0.9351
Number of observations	5,675	4,052

Standard errors (in parenthesis) are clustered by city-district in panels A and B and by city in panels C and D. ***: $p < 0.01$. Although not reported in the table, a constant is included in every regression. The regressions in column (1) of panels A and B include 3,500 city-district-year fixed effects; the regressions in column (2) of panels A and B include 3,225 city-district-year fixed effects. The regressions in column (1) of panels C and D include 1,874 cluster fixed effects; the regressions in column (2) of panels C and D include 1,410 cluster fixed effects. In the matched sample, observations are classified into the same cluster if they are in the same city, same district, same year, planned for the same type of land use, and the first 12 Chinese characters of their addresses are identical. The regressions in panel B allow each city with 100 or more observations to have a specific coefficient. The regressions in panel D allow each city with 50 or more observations to have a specific coefficient.

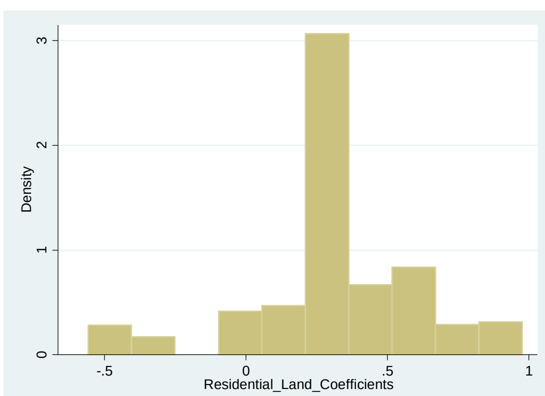
Figure 2: Distributions of city-specific coefficients



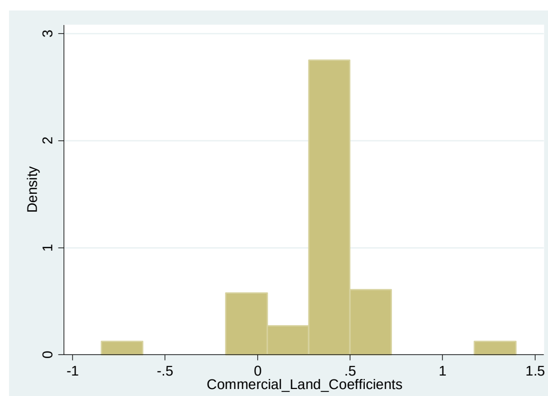
(i) 73 city-specific coefficients for residential land, full sample



(ii) 62 city-specific coefficients for commercial land, full sample



(iii) 38 city-specific coefficients for residential land, matched sample



(iv) 27 city-specific coefficients for commercial land, matched sample and Yingkou are well-known for their fast pace of urban construction. In recent years, they are often cited as examples of the Chinese housing bubble, having so many newly built but empty housing units that the cities are often referred to as "ghost cities."[15] These cities have small coefficients perhaps because they have been in a building spree where *FAR* restrictions are loose and thus often not binding. Xi'an, also with a small coefficient, is a city that has a long and rich history. It served as the capital of China during Zhou, Qin, Han, Sui, and Tang dynasties. More importantly, Xi'an is the only large city in China today that has preserved a magnificent city wall. The wall was constructed in the late 14th century, and it surrounds the present city center, being 12 kilometers in circumference, 12 meters high, and 15-18 meters thick at the base. While land is generally more valuable close to city center because it is closer to employment and many city amenities, planners may have imposed lower floor area ratios in this area to protect the beauty of the city wall and other historical sites in Xi'an. This mechanism implies a negative relationship between log land price and log *FAR*, which could cancel the positive correlation posited in our model and thus lead to a coefficient close to zero.

Cities with the largest coefficients include Nantong, Jiujiang, Kunming, Nanning, and Yancheng. These are all low-profile cities, whose relatively short buildings suggest that *FAR* limits are highly stringent. By contrast, it is perhaps somewhat surprising to see that the largest Chinese cities, such as Shanghai, Beijing, Tianjin, Chongqing, and Guangzhou, all have below-average coefficients. That is, despite the government's explicit policy to control growth in these mega-cities, their *FAR* limits do not seem to be more restrictive than those in many other cities.

4.3 Matched pair approach to address endogeneity of *FAR*

Our estimation so far is based on equations (14) and (15), which use city-district-year fixed effects to capture all unobserved site attributes. While this strategy allows us to use a large amount of data from more than 200 cities to estimate the relationship between log land price and log *FAR*, it may raise endogeneity concerns. As discussed in the model section, site attributes affect housing prices and in turn affect land prices. In addition, site attributes also affect the imposed *FAR* limit. Therefore, the coefficients from an OLS regression of log land price on log *FAR* are potentially biased due to omitted variables. In particular, noting that a city district is a rather large area (a typical city has 5 districts), two parcels in the same city district sold in the same year may still have different site attributes. For example, one parcel may be closer to the employment center. If planners choose the regulated *FAR* based on these site attributes, then the land price will be correlated with regulated *FAR* even if there is no causal link between them.

[15]Time magazine recently posted a set of photos of Erdos on its website (see http://content.time.com/time/photogallery/0,29307,1975397,00.html). They call it "a modern ghost town."

A standard approach to addressing this endogeneity issue is to use an instrument for regulated FAR. However, finding a valid instrument and collecting data from so many cities is not an easy task. Therefore, we take an alternative approach by controlling for a much more refined locational fixed effect. Our strategy is based on the observation that any city has simultaneous land development projects in close physical proximity. This proximity occurs either because a large piece of land is divided into subdivisions to be developed separately or because two or more parcels close to each other (e.g., across a street) happen to become available for development at roughly the same time. Our strategy is to identify all these small clusters of close-by land development projects and estimate the relationship between log land price and log FAR using within-cluster variations only.

The idea is that, if two parcels are next to each other, then it is reasonable to assume that they have very similar site attributes. However, even if the parcels have identical site attributes, planners may still impose different FAR restrictions on them, possibly for aesthetic reasons. For example, two identical buildings next to each other may not look attractive, and thus planners may intentionally impose a more-stringent FAR on one of the two parcels. No matter what drives the different FAR restrictions between the two parcels, it is important to note that this difference is not due to differential site attributes, given that we know such attributes are identical. Therefore, if we focus on variations among land development projects in close physical proximity and still find that higher FAR leads to higher a land price, then this effect is likely to be causal.

Two or more parcels of land are categorized into the same cluster if

- they are located in the same city, the same district, and sold in the same year;
- they have exactly the same land-use type;[16]
- the first 12 Chinese characters in their addresses are identical.[17]

The resulting regression has the same form as (15), with the city-district index d replaced by a cluster index. Since parcels that are not near other parcels are not part of a cluster, these parcels are dropped, leading to 5,675 observations in 1,874 clusters for the residential

[16] Even within residential or commercial land uses, there are many different specific use types. For example, within residential use, there are "residential housing," "ordinary housing," "affordable housing," "residential housing and retailing," "residential housing and daycare," "residential housing and public facilities," etc. We consider each use type a unique one as long as it is specified using a unique sequence of Chinese characters. This is a very narrow definition. For example, among Beijing's 327 residential land transactions, there are 138 distinctive use types by our definition.

[17] The address is taken from land-auction listings. Since information on province and city is self-evident in such listings, the address information starts with city district name, county name (in case it is a conversion of rural land to urban use), or street name. Since, at the time of land auction, the development project usually does not yet have a formal address, this variable often simply lists some streets as the boundaries of the land parcel. Two parcels for which part of the address or the whole address (in case the address is no more than 12 characters long) are identical are almost surely located along the same street or in the same village (if it is at the urban edge).

land sample and 4,052 observations in 1,410 clusters for the commercial land sample.[18] We will refer to these data as the matched sample.

Regression results using the matched sample are presented in panels C and D of Table 2. Panel C shows the results from single-coefficient regressions, which should be compared to those in panel A. For both residential and commercial land, the coefficient is now much smaller. For residential land, the coefficient is 0.3572, compared to 0.7466 estimated using the whole sample and controlling for city-district-year fixed effects. For commercial land, the coefficient is 0.3641 compared to 0.5669. Both estimates are still highly significant. These smaller coefficients indeed suggest that there is some omitted-variables bias in the coefficients estimated using the whole sample.

Panel D of Table 2 shows the results of the regression with city-specific θ coefficients estimated from the matched sample. To improve the precision of estimation, we only estimate separate coefficients for cities with at least 50 observations, with the other cities lumped together. Consequently, we have 38 city-specific coefficients for residential land and 27 coefficients for commercial land. Panels (iii) and (iv) in Figure 2 show the distributions of coefficients estimated using the matched sample, for residential and commercial land respectively. For residential land, the coefficients estimated using the matched sample are mostly smaller than those estimated using the whole sample; the distribution in panel (iii) looks like the one in panel (i) shifted to the left. For commercial land, the coefficients estimated using the matched sample not only have a lower average but also are more dispersed. We cannot tell how much of the increased dispersion results from the smaller size of the matched sample. Overall, most cities still have positive coefficients, as suggested by our model.

In the right column of the Appendix Table, we also list the 38 city-specific residential coefficients from the matched sample for comparison with those estimated from the whole sample. Xi'an, which has the second smallest coefficient in the left column, now has too few observations in the matched sample and does not have a separate coefficient. Erdos' coefficient becomes bigger. Qinhuangdao and Yingkou are now joined by Foshan, Shanghai, and Tianjin to form the top-five cities with the smallest coefficients. Looking down the lists, we see that the relative ranks of many cities have changed between the two sets of estimates. Zhengzhou, Harbin, Luzhou, Shenyang, and Huizhou have the largest coefficients in the right column. Overall, the estimates from the matched sample still show a great deal of heterogeneity across cites. Whereas FAR restrictions are not binding in some cities, they impose a serious constraint in other cities. In this latter group, housing density in newly developed communities would be higher if not for the stringent restrictions.

[18] For residential land, 66.49% of the clusters have only a pair of parcels, 22.41% have 3 or 4 parcels, and the rest (11.10%) have 5 or more parcels. For commercial land, 68.72% of the clusters have only a pair of parcels, 21.35% have 3 or 4 parcels, and the rest (9.93%) have 5 or more parcels.

Table 3: Regressions of FAR and its stringency on city characteristics

Variable	Residential Land FAR (1)	Commercial Land FAR (2)	Residential Land $\hat{\theta}_c$ (3)	Commercial Land $\hat{\theta}_c$ (4)
Log population size	0.0602*	0.1113***	0.0511	0.0606
	(0.0358)	(0.0398)	(0.0778)	(0.0607)
Log per capita city revenue	-0.1543***	-0.0996**	-0.0007	-0.0011
	(0.0369)	(0.0430)	(0.0794)	(0.0751)
Log per capita public buses	0.0962***	0.1202***	0.0645	0.0556
	(0.0342)	(0.0315)	(0.0734)	(0.0586)
Log per capita paved road area	-0.0901*	-0.0710*	-0.0766	-0.0778
	(0.0500)	(0.0484)	(0.1130)	(0.0954)
Constant	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No
Adjusted R^2	0.0880	0.0292	-0.0427	-0.0410
Number of observations	29,009	24,332	72	61

Standard errors are in parenthesis. In columns (1) and (2), standard errors are clustered by city. Regressions in columns (1) and (2) use city characteristics in the year of land lease auction; regressions in columns (3) and (4) use city characteristics in 2005. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

4.4 The empirical determinants of regulated *FAR* levels and their stringency

We next explore how the regulated FAR limits and estimates of their stringency vary across cities, analysis that is purely descriptive. From equation (19), we know that the planner's optimal FAR is determined by locational characteristics and the cost of complementary infrastructure, which in turn may be determined by city characteristics. Accordingly, we estimate the following equation:

$$\ln FAR_{jct} = \alpha + \tau_t + X_{ct}\beta + \mu_{jct}, \tag{20}$$

where FAR_{jct} is again a parcel-level FAR value, τ_t is a year fixed effect, and X_{ct} is a vector of city characteristics in year t.

Columns (1) and (2) in Table 3 present results for the regression in (20) using city population, per capita city revenue, public buses per capita, and paved road per capita to represent X_{ct}. While these characteristics vary from year to year, such within-city variations are small compared to cross-city variations, which thus drive the estimates. Note that running these regressions for individual land parcels (instead of at the city level) allows us to control for year fixed effects.

The results in the first two columns of Table 3 are qualitatively similar. Despite the low R^2, city characteristics indeed have some explanatory power. Larger cities tend to allow higher FARs, which makes sense since such cities are usually denser. For residential land, however, the coefficient of city size is only marginally significant, an outcome that may reflect the fact that the largest cities (Beijing, Shanghai, and Tianjin) have attracted many rich residents with demands for American or European style low-density suburban communities. With single-family houses at the urban fringe thus coexisting with high-rise apartment buildings closer to the city center, the lower than expected significance level of the population-size coefficient is perhaps understandable. Indeed, if we drop Beijing, Shanghai, and Tianjin, the coefficient of city size in the residential-land regression becomes more precisely estimated (p-value of 0.028 as opposed to 0.094 in the full sample).

The coefficient of the number of public buses per capita is highly statistically significant. Its positive sign is consistent with our model: when there are many buses in a city, new housing development is unlikely to strain the public transit system and therefore can be denser. On the other hand, per capita city revenue has a negative coefficient, which appears inconsistent with the model. However, a higher value of per capita city revenue may indicate a richer city and thus a demand for lower densities. Similarly, more paved road area per capita (which also leads to lower FARs) may be associated a higher degree of urban sprawl and thus low-density developments.

Next, we examine whether variation in the city-specific θ coefficients estimated from equation (15) can be explained by city characteristics. Since those coefficients indicate the stringency of FAR restrictions, one might suspect that they are also correlated with city characteristics. We regress the coefficients on the same set of city characteristics (measured in 2005) used in columns (1) and (2). The results, shown in columns (3) and (4) of Table 3, use the coefficients estimated from the whole sample ($\widehat{\theta}_c$) as dependent variable.[19] It turns out that observed city characteristics have no explanatory power in these regressions, with not a single city characteristic statistically significant and both adjusted R^2's negative (indicating poor fits). Therefore, results in Table 3 show that, although regulated FAR levels vary with observed city characteristics, their stringency cannot be explained by this same set of characteristics. Evidently, the regulatory regimes in different cities are motivated by unobservable factors, which lead them to choose different degrees of stringency in a manner uncorrelated with the current set of observables.

[19] We also ran parallel regressions using the coefficients estimated from the matched sample, and the results are similar.

5 Beijing Analysis

5.1 Land prices and regulated *FAR* in Beijing

We now turn to the city of Beijing and analyze the land-price effects of FAR restrictions within this single city. We estimate equation (16), which allows the elasticity of land price with respect to FAR to vary with site characteristics. To construct the sample for our analysis, we extract all of the 327 residential land parcels in the Beijing metropolitan area from the nationwide land-auction data. For each parcel of land, a detailed map is available from the online record of the land transaction, which we use to obtain its longitude-latitude coordinates. We then use GIS tools to construct site attributes, including the distance to employment centers, local infrastructure, and various amenities.

The first regression, shown in column (1) of Table 4, omits the interaction term in (16), regressing log land price on log FAR together with year fixed effects and site attribute variables, including distances to the CBD, the nearest major road, the nearest high school, and the nearest park. As in the regressions using the national data set, log FAR has a positive coefficient. In addition, the land price falls with distance to the CBD and distance to the nearest park, a pattern that persists in the other regressions in Table 4.

To cope with potential endogeneity, we instrument log FAR with dummies for each of the 17 districts in Beijing. The idea is that district governments may have different preferences for regulatory stringency, which are assumed to have no direct effect on land prices after controlling for site attributes. As seen in column (2) of the table, the two-stage least squares coefficient of log FAR is still positive and highly significant. Although the instruments pass the over-identifying test, the first stage F statistic (equal to 3.43) suggests a potential problem of weak instruments.

In columns (3) and (4), we interact log FAR with the distance to Tiananmen in both the OLS and 2SLS estimations. Tiananmen is at the center of a cluster of low-density historical sites and government complexes. The Forbidden City, Tiananmen Square, the Great Hall of the People, and Zhongnanhai (headquarters for the Communist Party and the State Council) are all within a mile of Tiananmen. Thus, we suspect that the stringency of the FAR limit is highest in the areas surrounding Tiananmen and declines moving away from it. Our regression analysis confirms this expectation. In particular, with negative estimated interaction coefficients, both the OLS and 2SLS results show that the coefficient of log FAR decreases with distance to Tiananmen, suggesting that FAR restrictions are less stringent farther away from this historical area.[20] Note that this conclusion also provides an internal check on the model's predictions. In particular, since FAR limits are known to be tight in the Tiananmen area, while the results show that this area has the highest elasticity of land price with respect to FAR, the link between stringency and this elasticity is independently

[20] For an attempt to estimate the cost of the building height restrictions in Beijing, see Ding (2013).

Table 4: Land price and FAR in Beijing

	Dependent Variable: Log unit land price			
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
Log FAR	0.647***	0.984***	3.800***	3.076***
	(0.151)	(0.135)	(0.981)	(1.108)
Log FAR*Log distance to Tiananmen			-0.306***	-0.194*
			(0.093)	(0.101)
Log distance to CBD	-0.381***	-0.323***	-0.283**	-0.244**
	(0.102)	(0.116)	(0.103)	(0.114)
Log distance to nearest major road	0.017	0.021	0.011	0.019
	(0.040)	(0.033)	(0.038)	(0.030)
Log distance to nearest high school	-0.019	0.018	-0.003	0.038
	(0.033)	(0.038)	(0.035)	(0.035)
Log distance to nearest park	-0.319***	-0.292***	-0.246***	-0.238***
	(0.063)	(0.068)	(0.084)	(0.093)
Constant	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
First-stage F statistic		3.43		
Sargan over-id test p-value		0.388		0.084
Number of obs.	327	327	327	327

Standard errors (in parenthesis) are clustered by city district. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. There are eight district dummies. Endogenous variable in Column (2): Log FAR. Instrumental variables in Column (2): 17 district dummies. Endogenous variables in Column (4): Log FAR and Log FAR*Log distance to Tiananmen. Instrumental variables in Column (4): 17 district dummies, Log distance to Tiananmen, and their interactions.

confirmed.[21]

5.2 Adjustment of *FAR* levels in Beijing

Complementing the analysis in section 4.4, this section provides a different perspective on the determinants of regulated *FAR* levels by exploring the factors that led to *adjustments* in *FAR* levels in Beijing over the 1999-2006 period. At issue is whether *FAR* adjustments respond to market pressures, reflecting a degree of efficiency in urban plannning. The analysis below uses the Detailed Planning Dataset (DPD) created by the Beijing Institute of City Planning, the government agency in charge of urban planning in the city of Beijing. In contrast to the CIA data used above, which exists because every local government has to release this information as it auctions the use right for a parcel, the DPD's information on *FAR* restrictions comes directly from the planning agency in the city of Beijing, having been tabulated regardless of whether its use right was transferred during our study period.[22]

In the empirical analysis below, we again study land parcels in residential and commercial uses and focus on those parcels that have the same land-use type in both the 1999 and 2006 plans. Our study sample includes 2,589 residential land parcels and 2,822 commercial land parcels. For residential land, the average planned *FAR* was 1.99 in 1999 and 2.23 in 2006; this ratio was adjusted upward for 35.9 percent of the parcels and adjusted downward for 10.1 percent of the parcels (see Table 5). For commercial land, the average planned *FAR* was 2.11 in 1999 and 2.36 in 2006; this ratio was adjusted upward for 34.3 percent of the parcels and adjusted downward for 21.4 percent of the parcels.[23]

[21] Instead of using the instrumental variable approach, we also tried to control for unobserved site attributes using location cluster dummies, as in the approach used above in Table 2. However, the sample size for clustered land parcels is very small: we can only identify 53 residential land parcels in 22 clusters in the Beijing area. The results similarly suggest that the *FAR* restrictions are less stringent further away from Tiananmen, but the estimates are imprecise because of the small sample size.

[22] In the earlier years of economic reform, detailed planning was applied only to land parcels that were designated for new development. Over time, because redevelopments became more and more common in built-up urban areas, many cities started to perform detailed planning for all land parcels. Beijing was one of the first cities to do so. First, in 1999, there was detailed planning for the Central Area of Beijing City, which consists of the districts of Dongcheng, Xicheng, Chongwen, Xuanwu, Haidian, Chaoyang, Fengtai, and Shijingshan. In 2010, the Xuanwu District was merged into Xicheng, and the Chongwen District was merged into Dongcheng. This Central Area was divided into 12,054 land parcels based on road networks, land ownership, etc. For each land parcel, the 1999 plan specifies its land-use type as well as development restrictions including building height, floor-area ratio, ratio of green space, and residential density. In 2006, there was another round of detailed planning in Beijing. This round covered not only the original Central Area (328 square kilometers, 15,207 land parcels) but also some suburban areas (281 square kilometers, 8,458 parcels). For each land parcel, the same kind of information is available as in 1999. Our analysis here focuses on the Central Area of Beijing covered by both the 1999 and the 2006 plans. Changes in planned *FAR*s between 1999 and 2006 are identified by spatially linking these two data sets. We overlay the centroids of land parcels in 1999 (the point file) with land parcels in 2006 (the polygon file) using ArcGIS. For each land parcel in 1999, its information in 2006 is obtained from the 2006 land parcel in which the 1999 centroid is located.

[23] There are mainly two types of changes in planned *FAR*s. The first type happened between 1999 and 2006 through negotiations between developers and planners. For this type of *FAR* change, we have no information about when the changes were made except for a few in 2001 and 2002 with clear documentation. The other type of *FAR* changes happened when planners reconsidered local conditions for each land parcel during the

Table 5: Floor area ratio changes between 1999 and 2006

	Residential Land		Commercial Land	
	Mean	Std Dev	Mean	Std Dev
FAR in 1999	1.993	0.602	2.107	1.937
FAR in 2006	2.234	0.873	2.359	1.513
	Observations	%	Observations	%
FAR increased	930	35.9	968	34.3
FAR unchanged	1,398	54.0	1,250	44.3
FAR decreased	261	10.1	604	21.4
Total	2,589	100	2,822	100

Land parcels included in the left column were specified for “residential” uses for both 1999 and 2006 plans; land parcels included in the right column were specified for “commercial” uses for both 1999 and 2006 plans.

For each land parcel observed in both 1999 and 2006, the DPD data contain information on local amenities, such as the distance to the city center, to the closest hospital, and to the closest park. This information is available for 2006 only, but the amenities are unlikely to have changed during the 1999-2006 period. However, access to the subway system is another important amenity, and because of dramatic expansion of the system in the early 2000s, access is likely to have changed over the period for a typical parcel. Fortunately, the DPD data contain the distance to the closest subway station in both 1999 and 2006.[24]

We examine changes in regulated floor area ratios in the city of Beijing in response to demand pressure, exploiting the exogenous variation created by the rapid expansion of the city’s subway system. The construction of the Beijing subway system started in the 1960s, and it evolved slowly during the next three decades. By 1999, the system consisted of only two lines: line 1 and the ring line. In 2001, Beijing was selected as the host of the 2008 Olympic Games, which spurred a massive construction of infrastructure in the city, including several new subway lines. By the end of 2003, line 13, line 5, and the Batong line

drafting of the 2006 plan. Either way, we are assuming that planners made the changes in response to perceived changes in local conditions.

[24] A map of areas covered by the 2006 planning, which is available on request, reveals a few facts worth noting: (1) Tiananmen (at the center of the map) and its surrounding areas have very low *FAR*s, consistent with the preservation of historical sites, as noted above; (2) The central business district and the financial district have mostly commercial land with very high *FAR*s; (3) *FAR*s are generally higher in the northwest than in the south. The third observation requires some explanation. In the Beijing area, rivers flow and wind usually blows from the northwest to the southeast. Historically, the southern part of the city was more dusty and occupied by the poor; the northwest was cleaner and occupied by the upper class and the royal families. Even today, the northwestern part of Beijing is still the more fashionable area to live in. It is less polluted than the southern part of the city. Universities and the high-tech sector are concentrated in the northwest, where the residents are more educated and the schools are better. For all of these reasons, land rent and housing prices are substantially higher in the northwest than in the south. According to our model, places with higher housing prices have higher optimal floor area ratios. It is thus not surprising that planners have allowed higher *FAR* in the northwest.

were put into service. By the summer of 2008, line 10, line 8, and the Airport line were also in operation. These dramatic changes altered the local conditions for many land parcels in the city. We take advantage of these spatially-varying shocks to investigate their effects on regulated FARs.

The estimating equation is

$$\Delta \ln FAR_{jd} = \rho_d + \phi \Delta D_{jd} + Z_{jd}\gamma + \upsilon_{jd}, \tag{21}$$

where $\Delta \ln FAR_{jd}$ is the change in regulated FAR for land parcel j in district d of Beijing, ρ_d is a district-specific intercept, ΔD_{jd} represents the change in distance to the closest subway station (as new subway lines are constructed), Z_{jd} is a vector of time-invariant locational characteristics, and υ_{jd} is the error term. We expect improved subway access to lead to an upward adjustment of FAR, so that $\phi < 0$.

Table 6 presents the regression results, starting with a simple specification where the change in log FAR between 1999 and 2006 is related only to the change in log distance to the nearest subway station, controlling for the 1999 log FAR level (columns (1) and (3)). The residential ϕ coefficient is negative and significant, indicating that, as expected, a reduction in distance to the nearest subway station leads to an upward adjustment in FAR. The ϕ coefficient in the commercial regression is also negative and of the same order of magnitude, although it is less precisely estimated. In both regressions, an initially high FAR level moderates the upward adjustment over the 1999-2006 period.

In an alternative specification (columns (2) and (4)), we further control for distance to the nearest subway station in 1999, distance to Tiananmen, distance to the 2nd Ring Road, distance to the nearest highway, distance to the nearest key middle school, distance to the nearest hospital, distance to the nearest park (with all distances in logs), and city district dummies. Although these local characteristics were hardly changing between 1999 and 2006 (being measured by 2006 values), changes in development pressure could have been correlated with local conditions, as measured by these variables. For residential land, the key subway access coefficient hardly changes after all these controls are added, still being negative and statistically significant. For commercial land, the key coefficient is also negative but again statistically insignificant.

Among the control variables, the positive and significant coefficient on log distance to Tiananmen shows that land parcels closer to this site are less likely to have their FARs adjusted upward between 1999 and 2006, in line with previous results. Distance to the Second Ring Road and distance to the nearest park also have significant coefficients in both samples, with FAR more (less) likely to be adjusted upward closer to the Ring Road (closer to parks), patterns consistent with casual observation. Note also that, for a given reduction in log distance to a subway station, the upward FAR adjustment is smaller the worse is the initial level of subway access (log distance to a station in 1999).

Overall, the results in Table 6 suggest that FAR restrictions tend be relaxed over time

Table 6: Regression of FAR changes, 1999-2006

Dependent Variable: Changes in log FAR between 1999 and 2006				
	Residential Land		Commercial Land	
	(1)	(2)	(3)	(4)
Change in log distance to nearest subway station	-0.0186**	-0.0166**	-0.0164	-0.0249
	(0.0061)	(0.0064)	(0.0101)	(0.0139)
Log FAR in 1999	-0.3307***	-0.376***	-0.2309***	-0.2603***
	(0.0311)	(0.041)	(0.0523)	(0.0482)
Log distance to nearest subway station in 1999		-0.0410**		-0.0958**
		(0.0167)		(0.0306)
Log distance to Tiananmen		0.1854***		0.1840***
		(0.0372)		(0.0513)
Log distance to 2nd Ring Road		-0.0362**		-0.0487**
		(0.0131)		(0.0164)
Log distance to nearest highway		0.0366		0.0493
		(0.0223)		(0.0267)
Log distance to nearest key middle school		0.0003		0.0160
		(0.0146)		(0.0123)
Log distance to nearest hospital		0.0017		0.0399**
		(0.0128)		(0.0148)
Log distance to nearest park		0.0238**		0.0469***
		(0.0081)		(0.0070)
Constant	Yes	Yes	Yes	Yes
District dummies	No	Yes	No	Yes
Adjusted R^2	0.0886	0.1241	0.0830	0.1435
Number of obs.	2,588	2,588	2,772	2,772

Standard errors (in parenthesis) are clustered by city district. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$. There are eight district dummies.

for residential land parcels in areas experiencing upward shifts in demand, as captured most prominently by improved subway access. This finding suggests that Beijing planners adjusted their regulations in response to market pressure, as economic efficiency would dictate.

6 Conclusion

Floor-area-ratio restrictions are the most commonly used planning tools in the regulation of housing development density in urban China. They help determine urban spatial structure and the extent of urban sprawl in China. However, little research has been done on this topic. In this paper, we have proposed a simple model to gain a better understanding of FAR restrictions. Our model suggests that relaxation of a binding FAR limit should raise the land price, and that the elasticity of price with respect to FAR is an indicator of the stringency of the restriction. The model treats FAR restrictions as a policy tool used by revenue-maximizing governments to limit the public infrastructure costs associated with new housing development. This view helps us understand why FAR restrictions are imposed and why they tend to be binding for developers. The model provides a useful framework for empirical research.

Drawing on information from two unique data sets, we show that land prices are indeed positively related to regulated FAR levels, and the results from a matched sample suggest that this relationship is likely to be causal. Second, the elasticity of land price with respect to FAR varies a great deal across cities, indicating considerable heterogeneity in the stringency of FAR restrictions. Third, cities with larger populations, lower government revenues, or higher dependence on public transportation (more buses per capita) tend to allow higher floor-area ratios. Fourth, within the Beijing metropolitan area, higher FARs again raise land prices, but the effect is weaker farther from Tiananmen, indicating that the restrictions become less stringent moving away from this historic area. Fifth, and finally, FAR limits in Beijing were adjusted upward as subway expansion improved a land parcel's subway access, suggesting that planners adjust their regulations in response to demand pressure.

The main contributions of this paper are twofold. First, our rich data allow us to demonstrate some important facts on FAR restrictions in China. Given the size of the Chinese economy and the speed of its transition, understanding the urbanization process in China is increasingly recognized as an important research goal. Second, this paper proposes a new way to measure the stringency of urban density restrictions. Following Glaeser et al. (2005), researchers have tried to measure the stringency of building-height limits by comparing the market value of an extra floor with its construction cost. We suggest an alternative method that measures the stringency of restrictions using the elasticity of land price with respect to the level of the restriction. The idea is straightforward: if the restriction is very stringent, then relaxing it will lead to a large increase in the land price. We expect this simple yet innovative idea to be useful for future research in other contexts.

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Appendix Table A-1: City-specific coefficients for residential land

Estimated using the full sample		Estimated using the matched sample
1. Qinhuangdao -0.011	41. Other cities 0.812	1. Foshan -0.557
2. Xi'an -0.011	42. Fuzhou 0.815	2. Shanghai -0.474
3. Erdos 0.027	43. Dongguan 0.827	3. Qinhuangdao -0.462
4. Kaifeng 0.103	44. Wuxi 0.841	4. Tianjin -0.269
5. Yingkou 0.120	45. Ningbo 0.843	5. Yingkou 0.000
6. Zhongshan 0.234	46. Guiyang 0.856	6. Kunming 0.003
7. Quanzhou 0.268	47. Changzhou 0.857	7. Anshan 0.006
8. Anshan 0.296	48. Langfang 0.867	8. Urumqi 0.098
9. Shanghai 0.316	49. Changchun 0.893	9. Nantong 0.112
10. Foshan 0.323	50. Shenzhen 0.894	10. Fushun 0.129
11. Ezhou 0.382	51. Weihai 0.904	11. Linyi 0.136
12. Yangzhou 0.425	52. Zhengzhou 0.908	12. Ezhou 0.180
13. Tangshan 0.428	53. Taizhou 0.913	13. Suzhou 0.205
14. Zibo 0.496	54. Fushun 0.928	14. Zhongshan 0.214
15. Linyi 0.510	55. Dalian 0.941	15. Chengdu 0.222
16. Guangzhou 0.538	56. Shenyang 0.945	16. Wuhan 0.242
17. Chengdu 0.547	57. Huaian 0.960	17. Weifang 0.246
18. Weifang 0.549	58. Nanchang 0.963	18. Ningbo 0.288
19. Suqian 0.564	59. Changsha 0.964	19. Yancheng 0.317
20. Suzhou 0.573	60. Xiamen 0.972	20. Hangzhou 0.321
21. Ji'nan 0.637	61. Daqing 1.005	21. Tangshan 0.327
22. Urumqi 0.659	62. Zhenjiang 1.026	22. Jiaxing 0.330
23. Lianyungang 0.662	63. Xuzhou 1.043	23. Other cities 0.333
24. Jilin 0.672	64. Harbin 1.084	24. Changsha 0.368
25. Tianjin 0.687	65. Jiaxing 1.085	25. Langfang 0.457
26. Huzhou 0.688	66. Nanchong 1.086	26. Lianyungang 0.466
27. Hohhot 0.702	67. Mianyang 1.114	27. Erdos 0.482
28. Huizhou 0.717	68. Changde 1.137	28. Qingdao 0.486
29. Beijing 0.724	69. Yancheng 1.242	29. Ji'nan 0.493
30. Jinzhou 0.735	70. Nanning 1.289	30. Quanzhou 0.506
31. Yantai 0.741	71. Kunming 1.318	31. Chongqing 0.547
32. Chongqing 0.744	72. Jiujiang 1.453	32. Dalian 0.554
33. Taiyuan 0.751	73. Nantong 1.554	33. Yantai 0.565
34. Luoyang 0.765		34. Huizhou 0.607
35. Hefei 0.768		35. Shenyang 0.756
36. Nanjing 0.775		36. Luzhou 0.852
37. Shaoxing 0.775		37. Harbin 0.863
38. Wuhan 0.788		38. Zhengzhou 0.978
39. Qingdao 0.799		
40. Hangzhou 0.802		

City-specific coefficients in the left columns are from the estimation of equation (15) using the whole sample; they correspond to the summary in panel B of Table 2. City-specific coefficients in the right column are from the estimation of the cluster version of (15) using the matched sample; they correspond to the summary in panel D of Table 2.