Land-Use Regulation and the Intensive Margin of Housing Supply

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October 23, 2019

Abstract

This paper proposes a method for estimating the extent to which density regulation causes the actual housing supply per land unit to deviate from the unconstrained amount, i.e., the impact of density regulation on the intensive margin of housing supply. To overcome the challenges that both the housing supply per land unit (which is a combination of quantity and quality measures) and its unconstrained amount are unobserved to the researchers, we extend the framework of Epple, Gordon and Sieg (2010) by explicitly allowing substitution between the quantity and quality inputs in the housing production function and by imposing a regulatory upper limit on the use of the quantity input. We show theoretically that the land share of the housing value can be used as a proxy for the stringency of the density regulation. We apply this method in our investigation of the stringency of floor-to-area ratio (FAR) regulation in urban China at the land-parcel level and find that the regulation imposes a significant binding constraint on the housing supply per land unit. We then explore the spatial and temporal variations of FAR regulation stringency. We also find that the FAR regulation stringency intensified the housing price appreciation that occurred during the economic stimulus period after 2008.

JEL Classification: R31; R52

Keywords: Density regulation; Housing production function; Land share; Floor-to-area ratios

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Introduction

A large body of literature has focused on investigating the causes and consequences of government regulations that restrict the amount, location, and shape of residential development. (For a review, see Gyourko and Molloy, 2015). Empirical research in this literature has mainly dealt with the land-use regulations that are associated with the extensive margin of housing supply, namely, the supply of land for new development. For example, many studies have found that various growth-control policies in the U.S. (e.g., urban service boundaries, moratoria on new building permits, long wait times to obtain building permits) have restrained the amount of land available for residential development and thus have reduced the ability of housing supply to adjust to demand changes.[1] However, in urban areas where housing sectors feature high-density built environments and the land supply is somewhat limited, understanding the effect of land-use regulations that restrain housing supply on the *intensive margin* – the housing production *within* a given land parcel – is also crucial to the study of the impacts of regulations on local housing supply and local real estate prices.

Three research papers (to our knowledge) have rigorously investigated the effects of land-use regulations that focus on the floor area supplied per land unit (or building density). The pioneering study is Glaeser, Gyourko and Saks (2005a) which suggests that the gap between per-floor-area housing price and marginal construction cost for residential buildings in Manhattan can be used as an index of the extent to which regulations restrict development density below market levels. Brueckner, Fu, Gu and Zhang (2017) estimates the elasticity of land price with respect to density limit, and shows that it is proportional to the ratio of the unconstrained and regulated construction

[1] See, for example, Katz and Rosen (1987), Rosa (1989 a, b), Quigley and Raphael (2005), Glaeser, Gyourko and Saks (2005b, 2006), Glaeser and Ward (2009), Saiz (2010), and Baum-Snow and Han (2019).

densities. Based on the estimates from a structural model of building density decisions made by private land developers, Cai, Wang and Zhang (2017) predicts the unconstrained density levels that would maximize land value and finds that these levels are much higher than the regulatory density limits in urban China, especially for land parcels in locations that are relatively more attractive. In this paper, we propose a new method for estimating the extent to which density regulation causes the actual housing supply per land unit to deviate from the unconstrained amount. Unlike the above three papers which measure the impact of density regulation on the floor area per land unit supplied, housing supply here is a combination of both quantity and quality. We contribute to the existing literature by providing a way to *directly* measure the impact of density regulation on the intensive margin of housing supply.

Our estimation encounters two empirical challenges. First, because housing production combines both quantity and quality inputs, the housing supply per land unit is unobservable. Second, the housing supply in the absence of regulation (i.e., the unconstrained amount) is also unobserved. To overcome these challenges, we borrow Epple, Gordon and Sieg (2010)'s method to estimate the housing production function while treating housing supply per land unit as a latent variable. (We will henceforth refer to that study as "EGS".)[2] Further, we extend EGS's framework by explicitly allowing substitution between the quantity and quality inputs in the housing production function. The density regulation takes the form of an upper limit imposed on the use of the quantity input. We show theoretically that the ratio of the unconstrained housing

[2] EGS provides an innovative approach for estimating the housing production function. This approach treats housing quantities and prices as latent variables. In particular, the study uses duality theory to derive an estimation specification that requires data on land values, lot sizes, and housing values. EGS's framework assumes that the housing production function satisfies constant returns to scale and therefore is able to normalize output in terms of land use. Using metro-level variation in both land and non-land costs, Albouy and Ehrlich (2018) also propose a method for estimating a housing cost function based on duality theory. They show that regulatory and geographic restrictions create a wedge between the prices of housing and its inputs.

supply relative to the constrained housing supply per land unit is positively associated with the land share of the housing value. As such, the land share of the housing value can be used as a proxy for the stringency of the applicable density regulations on the intensive margin of housing supply.

We use this method to investigate the stringency of floor-to-area ratio (FAR) regulations in urban China. A regulatory FAR level is a typical density restriction for land development that imposes an upper limit on the ratio of the total floor area to the lot size of the land to be developed. FAR regulations are common in both developed and developing countries.[3] In urban China, as a major form of land-use regulation, FAR regulations are designated and implemented by each city's urban planning bureau at the land-parcel level. Using a unique data set of residential land sales data matched with residential development projects from 25 major Chinese cities, we estimate the land share of the housing value for each land parcel conditional on its regulatory FAR upper limit and locational amenities. We find that the land share of the housing value decreases as the regulatory FAR level increases: a one-standard-deviation increase in FAR limit (1.23) from its sample average (2.56) leads to a decrease of the land share of the housing value by 0.06, representing about 20% of the average land share (0.31). This provides evidence that the FAR regulation has imposed a significant binding constraint on the housing supply per land unit.

We then explore how the FAR regulation stringency varies across locations and over time. Our estimates show that, on average, the FAR regulation stringency in the coastal cities is higher than that in the inland cities. The regulation stringency in both these city types has been declining over the years. By relating each parcel's land share

[3] See, for example, Fu and Somerville (2001), Bertaud and Brueckner (2005), Gao, Asami and Katsumata (2006), Gomez-Ibanez and Ruiz Nunez (2009), Bertaud (2011), Brueckner and Sridhar (2012), Brueckner, Fu, Gu and Zhang (2017), and Cai, Wang and Zhang (2017).

to the parcel-level characteristics, we find that larger land parcels located in more attractive neighborhoods are subject to greater FAR regulation stringency, although the regulatory FARs per se are higher for land developments located in more attractive locations. This suggests that although urban planners permit higher residential development density in locations with higher market demand, the gap between the planned density and its market driven counterpart still exists and it expands as one moves to more attractive locations within cities. Finally, we apply our stringency measure to a study of housing price changes. We show evidence that the FAR regulation stringency lowers a city's housing supply elasticity by investigating housing price appreciation across major Chinese cities during the economic stimulus period that occurred after 2008.

The rest of the paper is structured as follows. Section 2 presents the model and the estimation specification. Section 3 discusses the background of land development and FAR regulation in urban China. Section 4 describes the data. Section 5 reports the main results and shows the robustness checks. Section 6 explores the spatial and temporal variations in the FAR regulation stringency. Section 7 investigates the influence of regulatory stringency on housing prices in urban China. Section 8 concludes.

2. Empirical strategy

2.1 Theoretical framework

Our model builds upon the framework developed by EGS. We assume that all developers have the same production technology and that it exhibits constant returns to

scale.[4] Assume that developers are price takers.[5] Housing is a homogenous and perfectly divisible good denoted by H. A developer uses land (L) and a composite of all non-land factors (N) to produce housing services via a Cobb-Douglas production function,[6]

$$H = AN^{1-\beta}L^{\beta}, \tag{1}$$

where A represents the housing production productivity, and β is the land-share parameter. In (1), $A > 0$, and $0 < \beta < 1$.

The non-land factor N is composed of a quantity input, F, and a quality input, M:

$$N = M^{\gamma}F^{1-\gamma}, \tag{2}$$

where $0 < \gamma < 1$. Intuitively, F can be thought of as the capital necessary to build the total floor area of a building structure, while M is that necessary to improve the quality of the building.

From (1) and (2), we have the production function per unit of land:

$$h = A\left(m^{\gamma} f^{1-\gamma}\right)^{1-\beta}, \tag{3}$$

[4] The constant-returns-to-scale assumption is fairly standard in the literature on housing construction (Epple et al., 2010). Similar to EGS, Combes, Duranton and Gobillon (2017) develops a non-parametric estimation of the housing production function while treating housing as a latent variable. Unlike EGS, Combes et al. (2017) does not assume constant returns to scale. Their estimates suggest that the housing production function is reasonably well approximately by a Cobb-Douglas function with constant returns.

[5] As observed from the land auction data provided by Cai, Henderson and Zhang (2013), the number of developers in any major city is large. The assumption of price-taking developers is not uncommon in the literature (e.g., Saiz, 2010; Epple et al., 2010). We will conduct robustness checks regarding this assumption in Section 5.

[6] Although the Cobb-Douglas function form is a somewhat strong assumption, it provides a simple analytical function form that describes the relationship between the price per land unit and the housing value per land unit. In addition, this assumption is not uncommon in the literature and the rigorous studies using parcel-level data tend to suggest that the elasticity of substitution of land for capital is close to one and that a Cobb-Douglas form is a reasonable approximation of the housing production function (Thorsnes, 1997; Epple et al., 2010; Ahlfeldt and McMillen, 2014; Combes, Duranton and Gobillon, 2017).

where h represents the housing supply per land unit (i.e., H/L), m is the quality input per land unit (i.e., M/L), and f is the quantity input per land unit (i.e., F/L). Here, f corresponds to the total floor area per land unit (the FAR).

The density regulation imposes an upper limit $\bar{f}$ on the use of f. The developer can freely choose f until it reaches $\bar{f}$. The stringency of the density regulation, denoted by χ, is captured by the ratio of the unconstrained housing supply per land unit to the constrained housing supply per land unit:

$$\chi \equiv \frac{h^*}{h^c}, \tag{4}$$

where h^* is the optimal housing supply per land unit in the absence of any quantity restriction, and h^c is the optimal housing supply per land unit in the presence of the quantity restriction. In (4), χ is equal to one or larger than one. In the case where the density regulation is not binding housing production, χ equals one. In the case where the density regulation is binding housing production, χ is larger than one.

In equilibrium, the zero-profit condition defines the relationship between the price per land unit, p_l, and the housing value per land unit, v:

$$p_l = \tilde{\beta} v, \tag{5}$$

where

$$\tilde{\beta} \equiv \beta + \phi_1 (1 - \chi^{-\phi_2}). \tag{6}$$

In (6), $\phi_1 \equiv (1-\beta)(1-\gamma) > 0$, and $\phi_2 \equiv \beta / \phi_1 > 0$. See Appendix A for the deduction details. In (5), $\tilde{\beta}$ represents the gradient of unit land price with respect to housing value per land unit; namely, the land share of the housing value. In the unconstrained

equilibrium (i.e., $\chi = 1$), the land share of the housing value ($\tilde{\beta}$) equals the land-share parameter (β) in the housing production function. In the constrained equilibrium (i.e., $\chi > 1$), the land share of the housing value ($\tilde{\beta}$) increases with the stringency of the density regulation (χ). As such, the land share of the housing value can be used as a proxy for the stringency of the density regulation imposed on the housing supply per land unit.

In the constrained equilibrium, the following equality holds:

$$\chi = \left(\frac{f^*}{\overline{f}} \right)^{(1-\gamma)(1-\beta)/[\beta+(1-\gamma)(1-\beta)]} . \tag{7}$$

Eq. (6) and (7) depict an important relationship: when the regulation is binding, the land share of the housing value increases as regulatory limit $\overline{f}$ decreases, holding the unconstrained level of quantity input f^* fixed; otherwise, the land share should not change with $\overline{f}$.

2.2 Estimation specification

In our empirical analysis, we estimate the land share of the housing value at the land parcel level, conditional on the observed regulatory FAR upper limit and land location amenities at each land parcel. This estimated share can serve as a proxy for the stringency of density regulation as discussed earlier in the paper. Let the observed price per land unit for each land parcel be

$$\tilde{p}_l = p_l + \varepsilon_p , \tag{8}$$

where p_l represents the actual land cost paid by the land developer for the land parcel and ε_p is a measurement error.

The value of housing per land unit for development on each land parcel can also be measured with error

$$\tilde{v} = v + \varepsilon_v , \tag{9}$$

where v is the value of housing per land unit perceived by the developer and ε_v may reflect either measurement error or productivity shocks.

Plugging (8) and (9) into (5) gives us the following equation:

$$\tilde{p}_l = \tilde{\beta}\tilde{v} + (\varepsilon_p - \tilde{\beta}\varepsilon_v) . \tag{10}$$

To investigate how the land share of the housing value changes in response to a change in the regulatory FAR limit, we impose the following linear relationship based on (6) and (7) in Section 2.1:[7]

$$\tilde{\beta} = \theta_0 + \theta_1 \log FAR + z\theta_2 + \xi , \tag{11}$$

where FAR represents the upper limit of FAR imposed on each land parcel; z represents all the relevant locational amenities that affect the unconstrained FAR level;[8] ξ is an error term, which has zero mean and is assumed to be independent of the measurement errors in (8) and (9). When the FAR regulation is binding, $\tilde{\beta}$ should

[7] We also experimented with other functional forms such as the polynomials of the FAR limit. We found that only the linear term is statistically significant. We omit the results from the paper to save space but they can be provided upon request.

[8] DiPasquale and Wheaton (1996) suggest that the unconstrained FAR level is determined by the collective value of the relevant locational attributes, including distance to the city center, school quality, and access to public services such as subways, parks, hospitals, etc.

increase as FAR is lowered, holding z constant; otherwise, $\tilde{\beta}$ should stay unchanged as regulatory FAR changes.

Plugging (11) into (10), we have our main regression specification:

$$\tilde{p}_{li} = \theta_0 \tilde{v}_i + \theta_1 \tilde{v}_i \log FAR_i + \tilde{v}_i z_i \theta_2 + \tilde{u}_i , \tag{12}$$

where $\tilde{u}_i \equiv \xi_i v_i + \varepsilon_{pi} - (\theta_0 + \theta_1 \log FAR_i + z_i \theta_2)\varepsilon_{vi}$.

In (12), the subscript i denotes land parcel i. Using data on land price, house price, land parcel's regulatory FAR, and locational attributes, we can estimate (12). The estimate of θ_1 informs us whether the FAR regulation is binding housing production. Furthermore, the estimates of θ_k, k=1, 2, 3, help us estimate the land share of the housing value for each land parcel based on (11).

There are two identification problems regarding (12). The first one emerges from the measurement error in $\tilde{v}$ as discussed in EGS; that is,

$$\text{cov}(\tilde{v},\ \tilde{u}) = -(\theta_0 + \theta_1 \log FAR + z\theta_2) Var(\varepsilon_v) . \tag{13}$$

The OLS estimates, therefore, are inconsistent. To solve this endogeneity problem, we adopt EGS's strategy of constructing instruments from variations among the land's locational attributes, which are assumed to be uncorrelated with ε_v. Distances of land parcels from the city center, which are a systematic source of within-city variation in housing values, and city fixed effects, which reflect systematic differentials across cities in amenities as well as the quality of public goods, are used to construct an instrument for $\tilde{v}$. We will discuss details of this instrument construction in Section 4.

The second problem is caused by error term ξ in (11). If we fail to control for all of the relevant locational amenities that affect the unconstrained FAR, and if these

omitted variables also correlate with regulatory FAR, then ξ would correlate with $\log FAR$. This results in a correlation between $\tilde{v}\log FAR$ and $\tilde{u}$; that is,

$$\text{cov}(\tilde{v}\log FAR,\ \tilde{u}) = \text{cov}(v\log FAR,\ v\xi) - \theta_1(\log FAR)^2 Var(\varepsilon_v). \qquad (14)$$

In (14), the first term on the right-hand side may not equal zero if regulation FAR and ξ are correlated.[9] To address this problem, we exploit the uniqueness of the auction data as it provides the reserve price of each land parcel at auction, which is a comprehensive measure of the collective value of all locational amenities in the neighborhood of the parcel (Cai, Henderson and Zhang, 2013). We will discuss the institutional details of this variable in Section 3. Furthermore, as a robustness check, we will compare the land shares of land parcels located in adjacent neighborhoods to eliminate the endogeneity of regulatory FAR in Section 5.2.4.

3. Land development and FAR regulation in urban China

In China, all urban land is owned by the state. Since 1988, the use rights of vacant urban land have been allocated through leaseholds by 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. Since then, all urban leasehold sales for private development have been conducted through public auctions. In each city, land auctions are held by the local land bureau, with details of all transactions posted to the public on the Internet.

[9] The measurement error causes the additional correlation between $\tilde{v}\log FAR$ and $\tilde{u}$ as shown by the second term in (14).

The authority in charge of land use planning and general guideline setting is the city land reserve and allocation committee, whose members include the city's key leaders and bureau directors from relevant government agencies. The planning guidelines are made with the goals of promoting "rational" land use, guarding "public interests," and protecting historic heritage and natural resources. After setting up the urban development strategies and guidelines, the committee typically delegates the routine decisions regarding detailed regulations on each parcel of land to be developed (land use type, FAR, building height, green space ratio, etc.) to the city's urban planning bureau. When designing land use regulations, urban planning bureaus aim to maximize the value of land by weighing various social benefits and costs. For the determination of regulatory FARs, the bureaus consider both the market factors (e.g., demand and supply) and social factors (e.g., possible congestion costs arising from high-density development).

After the detailed land use regulations are specified and before each land parcel is released to the city land bureau for auction, the committee sets the reserve price for public land auction. In particular, the committee authorizes an independent appraiser to evaluate the land parcel to be auctioned. The appraisal factors in the city's social and economic conditions (e.g., population size, income level, family compositions, current housing stock), local government's housing policies, land's locational amenities (e.g., the distance to commercial centers, access to public goods such as schools, subways, parks, hospitals, etc.), land-use regulations, and geographic conditions (GAQSIQ, 2001, 2014). In general, the reserve price is a comprehensive measure of the collective value of relevant locational amenities (e.g., local demand and supply conditions, locational attributes, geographic conditions of the land parcel, etc.).

FAR regulation is one of the most important types of land use regulation in urban China. By law, any land parcel to be auctioned off must have a designated regulatory FAR. Also, after the land is developed but before the house units are sold, the city's planning bureau must complete an official inspection of the project to ensure compliance with the FAR regulation. In most 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. Cai, Wang and Zhang (2017) shows that FAR regulations have significantly restricted China's urban land development even given imperfect compliance.

4. Data, variable construction, and summary statistics

4.1 Land sale data

We collected the transaction data on residential land sales from the official listings posted on www.landlist.cn by local land bureaus. The raw data covers 9,394 completed land transactions from 30 major Chinese cities in the years 2002 through 2012. The basic information includes the land use type, lot size, reserve price, sale price, regulatory lot size for construction, regulatory total floor area, auction type, etc. For each land parcel, the regulatory FAR is calculated by dividing the land's regulatory total floor area by its regulatory lot size for construction. Additionally, we obtain the geographic coordinates for each land parcel from www.Soufun.com. Using these coordinates, we calculate the distance to the city center for each land parcel.[10]

[10] We use the coordinates of the 1992 light center (i.e., the brightest cell at night in each city's central area) from Baum-Snow et al. (2017) to identify the actual city center. They suggest that despite enormous increases in light over the past two decades, the light centers have not changed.

4.2 House sale data

The housing sector in urban China has been dominated by condominium units.[11] Residential buildings are usually grouped by residential development project. We refer to residential development projects as *RDPs* hereafter. (They are called "*xiaoqu*" in Chinese.) A typical RDP is built by a single developer on a contiguous land parcel. For all 30 cities in our land sample, we collected information on RDPs that had new property for sale as of May 2012 from www.Soufun.com. For each RDP, we have data on the average housing price per square meter of floor area in May 2012, referred to as *per-floor-area* price of RDP, and the geographic coordinates.

4.3 The matched samples

Using the coordinates of both land parcels and RDPs, we draw a ring that extends out 1.5 kilometers from the geographic center of each land parcel and we match all RDPs 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 6,027 residential land parcels with 4,727 RDPs.[12] The generally matched sample contains 4,184 unique land parcels that have no missing information on the key variables for the main regressions.

From the sample of generally matched pairs, we identify 625 *exactly matched* pairs in 25 of the 30 cities. These have no missing information on the key variables for the

[11] According to the National Bureau of Statistics, the nationwide percentage of condominium units in the newly-built market remained around 95% over the past 10 years (www.data.stats.gov.cn).

[12] On average, the 1.5-km ring of one land parcel contains about four RDPs. An RDP may fall into the rings of multiple land parcels. On average, each RDP belongs to the rings of five land parcels. We also redo the spatial matching using rings with smaller radii to improve the precision of the matching. The main results still stand. We discuss the details in Section 5.2.3.

regression analysis.[13] An exactly matched pair contains a land parcel and an RDP that is built only on this land parcel (i.e., the *ex-post* residential development).

The observed price per land unit for each land parcel in our sample is calculated as

$$\tilde{p}_{li} = \frac{\text{sale price of land } i}{\text{lot area of land } i}. \tag{15}$$

For each land parcel in the exactly matched sample, the observed housing value per land unit is calculated as follows:

$$\tilde{v}_i = \text{per-floor-area price of RDP on land } i \times \text{regulatory FAR of land } i. \tag{15}$$

For each land parcel from the generally matched sample, we use the average of the per-floor-area prices of the RDPs contained in the 1.5-km ring around the land parcel to serve as a proxy for the per-floor-area price of the RDP built upon it. The housing value per land unit is thus given by

$$\tilde{v}_i = \text{average per-floor-area price of RDPs near land } i \times \text{regulatory FAR of land } i. \tag{15'}$$

While it may have a greater measurement error in the housing value per land unit, the generally matched sample provides a much larger sample size for the regression analysis.

Figure 1 plots the time trends of land transaction volumes for the exactly matched and generally matched samples (left *y* axis in each panel). For comparison purposes, we also plot the total number of land sales through public auctions in the 25 cities reported in the *Yearbooks of Land Resource* (right *y* axis in each panel).[14] The overall

[13] They are Beijing (78), Changchun (3), Changsha (8), Chengdu (67), Dalian (35), Guangzhou (18), Ha'erbin (14), Hangzhou (35), Jinan (2), Kunming (6), Nanchang (37), Nanjing (59), Nanning (1), Ningbo (12), Qingdao (34), Shanghai (26), Shenyang (22), Shenzhen (8), Shijiazhuang (6), Taiyuan (9), Tianjin (46), Wuhan (24), Wuxi (63), Xi'an (3), and Zhengzhou (9). Numbers of observations are in parentheses.

[14] The data from the *Yearbooks of Land Resource* covers all residential, commercial and industrial land transactions.

trends are very similar. In all three samples, about 60% of land transactions occurred after 2008.[15]

Panels A and B of Table 1 report the summary statistics of the key variables for the exactly matched and generally matched samples, respectively. The land sale and reserve prices are converted to constant 2012 price levels using each city's hedonic quality-controlled home price CPI as provided by the *Hang Lung Center for Real Estate* at Tsinghua University. On average, the unadjusted land share is 0.39 for the exactly matched sample and 0.31 for the generally matched sample. For the exactly matched sample, the regulatory FAR limit has a mean of 2.36 and a standard deviation of close to one; for the generally matched sample, the mean of regulatory FAR is 2.56, and its standard deviation is 1.23.

Panel C of Table 1 presents the mean, median, 10th percentile, and 90th percentile of the regulatory FARs in each city using the generally matched sample. Regulatory FARs vary greatly across cities, with the upper limits of the coastal cities being much lower than those of the inland cities.[16] Within cities, regulatory FARs also vary largely across locations. Figure 2 plots the relationship between each land parcel's regulatory FAR and its distance to the city center for the four first-tier cities (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen) and the four largest second-tier cities located in the inland area (i.e., Wuhan, Nanchang, Zhengzhou, and Chengdu). In general, the regulatory FARs are monotonically decreasing in the distance to the city center.

[15] Note that the number of transactions in 2011 and later contained in the exactly matched sample is much smaller than those of the other two samples. This is because the land parcels that appear in the exactly matched sample are those for which we are able to locate their *ex-post* developments in our house sale data.

[16] For each city we also calculate the mean, median, 10th percentile, and 90th percentile in the distribution of regulatory FARs using a data set that covers all residential land transactions that occurred through public auctions from 2000 through 2011. This data set is provided by the *China Index Academy*, China's largest independent think tank focusing on the real estate market. Figure A1 in the appendix shows that all percentiles of regulatory FAR calculated from these two data sources are quite similar, suggesting that our sample is representative of the regulatory environments of the 25 cities.

4.4 Constructing instrument for housing value per land unit

To solve the problem of the measurement error in the observed housing value per land unit, we construct an instrument for $\tilde{v}$ following EGS's strategy. In particular, we first predict the per-floor-area price of RDP from the log of the land's distance to the city center and the city fixed effects. (Table A1 in the appendix reports the regression results.) We then multiply the predicted per-floor-area price of RDP by the land's regulatory FAR to create the instrumental variable for $\tilde{v}$, denoted by $\hat{\tilde{v}}$.

5. Estimation results

5.1 The effect of regulatory FAR limit on land share

In the regression model, in addition to $\tilde{v}$, we include the interaction of $\tilde{v}$ and the regulatory FAR limit (in log) as well as the interaction terms of $\tilde{v}$ and the variables that measure the land's locational amenities (z). We use each land's distance to the city center (in log) to partially control for z as it is one of the most important within-city location attributes that affect building density and is widely used in the literature (DisPasquale and Wheaton, 1996). To address the concern that other important neighborhood characteristics may still be omitted, we exploit the uniqueness of the auction data as it also provides the reserve price of each land parcel at auction. As discussed in Section 3, the reserve price of each land parcel is a comprehensive measure of the collective value of all locational amenities that affect the unconstrained densities. Furthermore, climate and land surface conditions may affect the technical standards of housing construction (Runeson, 1988; Sanders and Philison, 2003; Saiz, 2010) and hence constrain housing density. In all regressions, to address the concern that the regulatory FAR limits may be correlated with climate and geographic variables, we

additionally include the interaction terms of $\tilde{v}$ and the related city-level natural amenity variables (i.e., the maximum temperature, the minimum humidity, the roughness of the land surface, and the range of land elevation).

Columns 1 and 3 of Table 2 report the OLS results of (12) for the exactly matched and generally matched samples, respectively. To solve the problem of the measurement error in the observed housing value per land unit, we conduct the 2SLS estimation on regression model (12). For implementation purposes, we multiply the constructed instrument for the housing value per land unit ($\hat{\tilde{v}}$) by the regulatory FAR, distance to the city center, and land reserve price (all in logs), and the city-level natural attributes (respectively) to create the instruments for the interactions of the housing value per land unit ($\tilde{v}$) and the corresponding variables. Columns 2 and 4 report the 2SLS results for the exactly matched and generally matched samples, respectively. The standard errors are clustered at the year of land transaction. The coefficient of the interaction term of the housing value per land unit and the log of regulatory FAR captures the effect of the regulatory FAR on the land share of the housing value, which is negative and significant (or marginally significant) after the land's locational amenities are controlled for. Note that the estimation using the generally matched sample is more precise due to its large sample size. In addition, the instruments become stronger when using this larger sample. Column 4 of Table 2 shows that a 100% increase in the FAR limit lowers the land share by 0.124. This implies that a one-standard-deviation increase in FAR limit (1.23) from its sample average (2.56) is associated with a decrease in the land share of the housing value by 0.06, representing about 20% of the average land share shown in Panel B of Table 1 (0.31).[17]

[17] To experiment with alternative functional forms of specification (12), we replace the log of regulatory FAR with the FAR level. The estimates not reported here suggest that a one-standard-deviation increase

In our matched sample, while the housing data covers RDPs that had new development units for sale in May 2012, the land data is largely historical, consisting of land sales that occurred between 2002 and 2012.[18] Ideally, instead of the historical land sale prices, we would like to use the current market values of land parcels. Given the institutional changes that occurred in urban markets during the 2000s, the deviation of historical land sale price from the current market value may vary over the years. These year-specific effects may be captured in the measurement error of the observed price per land unit. If these year effects also correlate with housing value per land unit (i.e., the city government may sell land further away from the city center in later years), the estimation would be biased. To address this concern we control for both the land transaction year dummies and the city-specific linear year trends in all regressions.[19]

5.2 Robustness checks

In this subsection, we conduct several robustness checks to address various concerns regarding our identification strategy. For this exercise, we use the generally matched sample to ensure a large sample size for each regression. The results are reported in Tables 3, 4 and 5.

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in the regulatory FAR limit (about 1.2) lowers the land share of the housing value by 0.03, representing about 10% of the average land share of 0.31.

[18] Although the information on the starting time of each RDP development is not available, based on our interviews with people in the real estate industry, most of the RDPs in our data probably started development between 2007 and 2012, given the time needed for development and marketing. Because city governments typically allow two years between a land sale and the commencement of development, it is not unreasonable to see some RDPs in our housing data matched with land parcels sold in 2005. However, only a very small proportion (5.2%) of the land sales in the exactly matched sample occurred in 2004 or earlier. One possible explanation for this is that when those land parcels were sold, the existing structures on them had not been cleared and the residents living there had not been relocated. This may well have delayed land development.

[19] The main results still stand if we instead control for the city-specific transaction year dummies, but the first-stage *F*-stat drops below 10.

5.2.1 Existence of non-binding cases

In cases where regulation does not bind housing production decisions, the land share will not vary with the FAR limit, and it should be smaller than the land share in cases where the regulation is binding. Therefore, the baseline regression may underestimate the effect of regulatory FAR on the land share of the housing value, considering the existence of the non-binding cases in our regression samples. We conduct three robustness checks to address this concern.

First, to investigate how this possibility affects our estimation, we run regressions with the less-likely binding subsamples. Specifically, we calculate the land share for each land parcel using the estimates of θ_k, k =1, 2, 3, returned from the baseline regression (12) using the full sample (column 4 of Table 2). The less-likely binding subsamples are those that contain the land parcels whose land shares lie in the lower percentiles of the distribution of the estimated land shares. For example, the "bottom 30%" subsample would be more likely to contain a higher percentage of non-binding cases than the "bottom 40%" subsample. Table 3 reports the estimates using different bottom-decile subsamples. The estimates of the effect of regulatory FAR on land share remain little changed across these subsamples, except for the bottom 20% and 10% subsamples. This may be due to the existence of a large percentage of non-binding cases in these two deciles.

Second, we identify the non-binding cases among the generally matched sample using the estimates from Cai, Wang and Zhang (2017) which estimates a structural model of FAR decisions made by private developers subject to regulations. In particular, based on these estimates, we predict the FARs that would maximize land values in the

absence of regulation ("unconstrained FAR") and the FARs chosen by the developers subject to regulation ("constrained FAR") for our generally matched sample.[20] The non-binding cases are those having identical unconstrained and constrained FARs, which account for about 18% of the land developments in our sample. The rest are the binding cases where the unconstrained FARs are strictly higher than the constrained ones. We then re-run the regression by excluding these non-binding cases. As shown in column 1 of Table 4, the main results shown in column 4 of Table 2 still stand.

Third, as the land share of the housing value increases as one moves closer to the city center (Table 2), the density regulations would be more likely to be binding in the central city area. We thus re-run the main regression with the land parcels that are located within a 15-km radius of the city center. As shown in column 2 of Table 4, the estimates are similar to our main results.

5.2.2 Competitiveness of land market

Cai, Henderson and Zhang (2013) show that land sale prices and competition are significantly less for land transactions that involved favored bidders. The existence of the non-competitive sales challenges the assumption of a perfectly competitive land market. Theoretically, we can relax this assumption in the model and allow those developers with certain degree of market power in the land market to enjoy a discount in land cost, denoted by τ, $\tau > 0$. That is, $p_l = \tilde{\beta} v - \tau$. Empirically, we use a dummy variable that indicates whether the land parcel was sold by a non-competitive sale to capture τ. We define a non-competitive sale to be the land transaction with the ratio

[20] For the generally matched sample, the constrained FARs are predicted from Cai, Wang and Zhang (2017) since we are unable to observe them from our data. Figure A2 plots the unconstrained FARs against the constrained ones for the generally matched sample.

of sale price to reserve price being below 1.005, following Cai et al. (2013). We then re-run the regression corresponding to (12) by further including the non-competitive-sale dummy. Column 3 of Table 4 reports the results. The estimates of the baseline regression remain robust.[21] In addition, our main results remain unchanged to excluding the non-competitive sales.[22]

Two-stage auctions and English auctions are the main auction types that local land bureaus use. Cai et al (2013) finds that a corrupt government official is more likely to select the former type as it has a first stage in which her favored developer signals that the auction is taken, deterring the entry of other bidders. Corrupt land sales cost land developers extra money to bribe local officials. This extra cost causes a gap between the actual unit land cost (p_l) and the observed price per unit of land ($\tilde{p}_l$). To capture this gap, we re-run the regression corresponding to (12) by further including a dummy variable that indicates whether the land parcel was sold through a two-stage auction. Column 4 of Table 4 reports the results. The estimates of the baseline regressions remain unchanged.[23]

5.2.3 Spatial correlation in the generally matched sample

The way we construct the generally matched sample may mechanically cause a spatial correlation between the land parcels that are matched with the same RDPs. To address this concern, we re-do the spatial matching described in Section 4.3 using rings

[21] The coefficient on the non-competitive-sale dummy, omitted from the table to save space, suggests that land parcels that went through non-competitive sales, on average, are sold for 4,000 yuan less per square meter than land sales that went through competitive sales.
[22] The results are available upon request.
[23] The estimate on the two-stage dummy, omitted from the table to save space, suggests that land sales that occurred through two-stage auctions, on average, are sold for 1,300 yuan less per square meter than land sales that occurred through English auctions.

with smaller radii to improve matching precision. In particular, instead of using a 1.5-km ring, we draw a 0.5-km ring around each land parcel and match all RDPs located in this smaller ring to the land parcel. We thus match 2,574 land parcels with 2,214 RDPs.[24] Although the sample size shrinks, the observations in the new matched sample are less likely to be correlated. As shown in column 5 of Table 4, the estimates using this new matched sample are similar to the main results.[25]

In addition, we re-run the main regression with the original generally matched sample and generate standard errors by bootstrap replications. Column 6 of Table 4 reports the results. The main results still stand.

5.2.4 Comparing regulation stringency of land pairs in the same neighborhood

Readers may worry that reserve prices cannot fully address the omitted locational amenities and thus the 2SLS estimates in Table 2 are still biased. To address this concern, we conduct a robustness check to directly compare the land shares of land-development pairs located in adjacent neighborhoods, assuming that each pair shares similar locational amenities. Specifically, based on the geographic coordinates of land parcels from the generally matched sample, we match each parcel with the nearest other parcel. We further restrict the sample to include the land pairs with pairwise distances of 500 meters or less that were sold in the same year.[26] This strategy creates a sample of land pairs whose unobserved locational amenities (those that affect the unconstrained FARs) are likely to be similar. With this land-pair sample, we run the following regression:

[24] On average, each RDP belongs to the rings of 1.7 land parcels. 60% of RDPs belong to only one ring, and 25% fall in two rings.
[25] The results are similar if we instead fix rings at 400 meters or 300 meters.
[26] For regression analysis, we further drop the duplicates of land pairs.

$$landshare_i = \psi \log FAR_i + \text{pair fixed effects} + \omega_i , \qquad (16)$$

where $landshare_i$ is the ratio of per-unit land price to housing value per land unit; FAR_i is the regulatory FAR level; ω_i is an error term. The estimate of ψ tells us how much the land share would change in response to an increase in regulatory FAR, holding everything else equal. Note that since pairs are year-specific, year fixed effects are not needed. We report the results in column 1 of Table 5. A 100% increase in the FAR limit lowers the land share by 0.129, which is similar to the estimated effect in our main analysis (column 4 of Table 2). We also run regression (16) using land pairs within narrower distance bands (i.e., 400 meters or less, or 300 meters or less). The results remain similar (see columns 2 and 3 of Table 5).[27]

5.2.5 Imperfect competition in housing market

Some large developers may be able to affect housing prices in local markets. We use a simply way to model an imperfectly competitive housing market. In such market, each developer faces a downward sloping demand curve:

$$p_h(h) = Bh^{-\alpha} ,$$

where B is a positive constant, and α is the inverse of the elasticity of housing demand with respect to housing price (in absolute value), $\alpha > 0$. The greater the developer's market power, the bigger α is by standard microeconomic theory. In perfect competition, α equals zero. All the other economic environment remains

[27] Table A2 in the appendix shows that the observed locational variables are similar across land parcels within pairs. In addition, the lot size, which is likely correlated with the overall environment of a residential development, is also similar within pairs.

unchanged. We can theoretically prove that in equilibrium the relationship between the price per land unit and the housing value per land unit is as follows:

$$p_l = \tilde{\beta}^{nc} v,$$

where

$$\tilde{\beta}^{nc} \equiv 1-(1-\beta)(1-\alpha)\gamma-(1-\beta)(1-\alpha)(1-\gamma)\chi^{-[1-(1-\beta)(1-\alpha)]/(1-\gamma)(1-\beta)}.$$

Therefore, the positive relationship between the land share of the housing value and the stringency of the density regulation still holds as long as $0<\alpha<1$.[28]

Furthermore, the model implies that the relationship between land share $\tilde{\beta}^{nc}$ and regulation stringency χ will be attenuated as the market power of developer (α) increases. This implies that, holding the locational characteristics that determine the unconstrained FAR levels constant (f^*) constant, the effect of regulatory FAR ($\overline{f}$) on land share becomes smaller (in magnitude) as the market power of developers increases. To show consistent evidence, we resort to the matching sample discussed in Section 5.2.4 to better isolate the effect of the locational amenities that affect unconstrained FAR. In view that developers with a significant market power tend to be those who buy the land parcels with top sale prices, we re-run the regression corresponding to (16) while excluding the land pairs with at least one land parcel that is in the top quarter of sale prices in each city in each year. Columns 4-6 of Table 5 report the results. The effect of regulatory FAR on land share is slightly larger in magnitude for this subsample, consistent with the prediction. In this sense, our baseline estimate would be a lower

[28] The details of the proof are available upon request.

bound of the effect if the assumption of a perfectly competitive housing market does not hold.[29]

6. Spatial and temporal variations of FAR regulation stringency

How does the stringency of FAR regulations vary across land developments in our sample? What are the spatial and temporal patterns of the stringency variation? In this section, we calculate the land share for each of the 4,184 land parcels in our generally matched sample based on equation (11):

$$\hat{\tilde{\beta}}_i = \hat{\theta}_0 + \hat{\theta}_1 \log FAR_i + z_i \hat{\theta}_2 .$$

The estimates of θ_k, $k = 1, 2, 3$, are obtained from column 4 of Table 2. We then relate the estimated land shares to various land characteristics.

Panel A of Figure 3 separately plots the average land share in each year for the coastal and inland cities in our sample, weighted by the lot size of each land parcel. In all years, the average stringency in the coastal cities is greater than that in the inland cities. Furthermore, in both types of cities, the FAR regulation stringency has been declining. Panels B and C of Figure 3 show the time trends of land location and regulatory FAR limits in both types of cities. On average, the land parcels sold in the later years are located further away from the city center and subject to higher regulatory

[29] We conduct two additional checks. First, we re-run the regression corresponding to (12) excluding the top quarter of land parcels with the highest sale prices in each city in each year. The main results are robust. Second, we consider the local housing markets having a per-capita unsold floor area below the median (0.2) to be less competitive. The information on the total floor area of unsold housing units in each city in each year is from the website of China Real Estate Information, which is affiliated with the State Information Center, and the data on each city's annual urban hukou population is from the *City Statistical Yearbooks*. We re-run the regression corresponding to (12) excluding the land parcels sold in the less competitive local markets as defined above. The main results remain robust. The results are available upon request.

FAR limits, which may be the main driver of the downward trend in regulation stringency shown in Panel A.

To explore the determinants of FAR regulation stringency within cities, we regress the estimated land share on parcel-level characteristics. In addition to the parcel-level characteristics, we include in the regressions the land transaction year dummies, transaction quarter dummies, city-specific linear year trends, and city fixed effects. Table 6 reports the results. The results in column 1 suggest that larger land parcels located in more valuable neighborhoods (e.g., closer to the city center or having a higher land reserve price) are subject to greater FAR regulation stringency. This is consistent with the findings of Cai, Wang and Zhang (2017), which shows that regulatory FAR limits in urban China are much lower than those that would maximize land value, especially for land parcels in more attractive locations. This also echoes Brueckner et al. (2017), which examines FAR regulations in Beijing and finds that the stringency of FAR limits is greatest in the areas surrounding Tiananmen Square (the city center of Beijing) and declines as one moves away from it. One rationale for local planners to impose stricter land-use constraints in such valuable locations is to protect views of historical structures. Another is that the negative externalities from new dense developments in those locations may be large due to the dense historical residential buildings there (e.g., noise, traffic jams, limited provision of public goods such as primary school capacity).

The results from column 1 also suggest that the stringency is reduced if the land parcel is planned for mixed use (i.e., combined residential and commercial use). Column 2 presents the results using a subsample for which subway information is available. The results shown in column 1 are robust to further including the dummy variable indicating the presence of a subway stop within a 2-km radius of the

development. In addition, column 2 shows that the stringency is lower if there is a subway stop in the vicinity of the development. By studying the adjustments in regulatory FAR levels for existing properties in Beijing, Brueckner et al. (2017) documents that FAR regulation tends to relax over time for residential land parcels in areas experiencing upward shifts in demand (i.e., improved subway access). Our findings complement theirs by providing the cross-sectional evidence that Chinese urban planners adjust regulations in response to market incentives.

We next re-run the regressions in columns 1 and 2 of Table 6 using the regulatory FARs as the dependent variable. The results are reported in columns 4 and 5 of Table 6. The estimates show that regulatory FARs are higher for the land developments that are near public transit and planned for mixed use, and lower for those occupying larger lot areas, mirroring the coefficients in columns 1 and 2. By contrast, the regulatory FARs per se are higher for land developments located near the city center or having higher reserve prices. Compared with the results in columns 1 and 2, the estimates here suggest that although urban planners allow higher residential development densities in locations with higher market demand, the gap between the planned density and its market-driven counterpart still exists and it expands as one moves to more attractive locations within cities. In columns 3 and 6 of Table 6, we also report the results of the regressions that control for the city's population size and land area while excluding the city fixed effects. The estimates show that on average the FAR stringency (regulatory FAR) is higher (lower) in more populated cities.

7. FAR regulation stringency and housing supply elasticity

How would the FAR regulation stringency affect the ability of housing supply to adjust to demand changes (i.e., the housing supply elasticity)? As shown in Appendix B, the housing supply elasticity with respect to price is $(1-\beta)/\beta$, which would remain unchanged regardless of the FAR constraints, as long as the developers use the same housing production technology. In this section, we present an extension of the model in which the developer switches to a more land-intensive technology when the FAR constraint is overly stringent, causing the housing supply elasticity to decrease.

Suppose that initially, all the developers use the current technology and reach the constrained equilibrium with zero profits. Suppose now that there is another alternative technology available with higher land share $\beta_A > \beta$ in the housing production function. For example, developers may adopt a plan to build low density villa-like communities. A developer may be able to obtain positive profits by switching to the new technology. However, the change of technology involves a fixed adjustment cost. We show in the Appendix C that the potential gains from switching increase with the stringency of constraints such that when the constraints are strong enough, the gains exceed the switching cost and the developer switches to the new technology. Once they have switched, developers bid up the land price and a new zero profit equilibrium is established. The housing supply elasticity now becomes $(1-\beta_A)/\beta_A$, which is smaller than before. Therefore, we can conclude that when the FAR constraint becomes more stringent, the housing supply elasticity may decline.[30]

[30] This extended model still implies a monotonic relationship between the land share of housing value and the restriction stringency. Specifically, the land share of housing value increases from β to $\tilde{\beta}$, and further to β_A as the FAR regulation stringency gets tighter. Empirically, this means that the land share of housing value can still be used as a proxy variable for the stringency of FAR regulation, even if we allow developers to adopt new production technologies in response to more stringent FAR regulation.

In view of the effect of FAR regulation stringency on the housing supply elasticity as discussed above, we apply our stringency measure to a study of housing price changes. Since the mid-2000s, the escalation of residential housing prices in urban China has been remarkable. Figure 4 plots the trends of the hedonic quality-controlled home price index of the 25 cities in our sample, obtained from the Hang Lung Center for Real Estate at Tsinghua University. The average hedonic home price increased by 5.6% annually between 1997 and 2008. Despite the influence of the 2007 global financial crisis, the average hedonic home price increased by 16% annually between 2008 and 2011. It is hotly debated by the public whether this unprecedented housing price appreciation during the post-2008 period is associated with the 2008 Chinese Economic Stimulus Program.

On November 9, 2008, the central government of China announced an economic stimulus package of four trillion RMB (equivalent to 586 billion USD) to minimize the influence of the global financial crisis. The "Four Trillion Program" aims to boost investment by injecting vast financial resources into state-owned banks during 2009-2011. Figure 5 shows that, for the 25 cities in our sample, the average growth rate of bank loans dramatically declined in 2008, quickly bounced back in 2009, and peaked in 2010.[31]

Some critics have asserted that the program pumped excessive investments into a fragile economy and created bubbles in the real estate markets (Ouyang and Peng, 2015). If the stimulus program did bring over-investment into local real estate markets and boosted housing demand during 2008-2011, the cities with more stringent FAR

[31] The bank loan variable measures the total amount of RMB that had been loaned to enterprises and individuals by banks and other financial institutes at the end of each year. The data are from the *City Statistical Yearbooks 2002-2012*.

regulations and thus smaller housing supply elasticities would experience greater housing appreciation in response to positive demand shocks.

We use the annual growth of total bank loans in each city to proxy for the degree of the city's demand shock. To measure each city's FAR regulation stringency, we use the estimated land shares from Section 6. For each of the 25 cities, we calculate the average land share of land parcels sold from 2005 through 2011, weighted by each land parcel's lot size. We run the following regression to investigate whether the effect of the local demand shock on housing price appreciation rate is intensified by an inelastic local housing supply due to stringent FAR regulation.

$$grhp_{c,t} = \mu_0 grbankloan_{c,t} + \mu_1 grbankloan_{c,t} \times \tilde{\beta}_c + \kappa_c + \eta_t + e_{c,t}, \tag{17}$$

where $grhp_{c,t}$ is the growth rate of housing prices in city *c* from year *t-1* to *t*; $grbankloan_{c,t}$ is the growth rate of bank loans in city *c* from year *t-1* to *t*; $\tilde{\beta}_c$ is the average land share in city *c*; κ_c are the city fixed effects, which capture the city's time-invariant characteristics that affect housing price appreciation; η_t are the year fixed effects; and $e_{c,t}$ is an error term. In (17), μ_1 is the parameter of interest. If a city's FAR regulation lowers its housing supply elasticity, we expect that $\mu_1 > 0$.

For the regression analysis, we construct a panel of the 25 cities from our sample, in which each city has three time intervals: 2008-2009, 2009-2010, and 2010-2011. The regression results are reported in Table 7. The average effect of the demand-shock measure on housing appreciation rate is positive but insignificant (column 1). Column 2 shows that the cities with more stringent FAR regulations and thus smaller housing supply elasticities experienced greater housing appreciation in response to positive local demand shocks. Together with the results from Section 5, we find that, if a city's

bank loans grow at the sample average (41.2 percentage points), an increase in the regulatory FAR limit by one standard deviation from its sample average is associated with a decrease in the housing price appreciation rate of 3.4 percentage points, which is 20% of the sample's average housing price appreciation rates (14.8 percentage points). In column 3, we replace the city's average land share with its average regulatory FAR. The estimates show that cities with higher FAR limits experienced smaller increases in local housing prices in response to positive demand shocks.[32]

8. Conclusions

This paper proposes a new method for examining the effect of land-use regulation on the intensive margin of housing supply, which is a combination of both quantity and quality. We show that the land share of the housing value can be used to measure the extent to which density regulation causes the actual housing supply per land unit to diverge from the unconstrained amount. Using a unique set of residential land sales data matched with residential development projects from 25 major Chinese cities, we measure the stringency of FAR regulation for each land parcel from our sample. The results suggest that even though urban planners allow higher residential densities in locations with higher market demand, the gap between the planned density and its market-driven counterpart still exists and it expands as one moves to more attractive locations. Our data also suggest that the FAR regulations exerted a non-negligible

[32] While we focus on the supply effect in the short term, a city's long-term housing supply should be affected by land-use regulations that target both the intensive and extensive margins. To explore the supply effects from both the intensive and extensive margins, we re-run the regressions in Table 7 by further including an interaction term between a city's annual bank loan growth rate and its developable land area (in log). We find that although the estimates become only marginally significant due to the limited sample size, the magnitude of the effect of FAR regulation remains. In addition, the coefficient on the interaction term between a city's annual bank loan growth rate and the log of the city's developable land area is negative but insignificant. The results are available upon request.

influence on housing markets in urban China during the economic stimulus period after 2008.

Policymakers in China have resorted to demand-side solutions to slow down housing price appreciation in several large coastal cities (e.g., banning non-registered residents from purchasing houses and raising down-payments required for second homes). However, these policies appeared to only temporarily suppress the demand for housing in these cities and failed to stabilize the overheated markets. Our results suggest that the housing supply constraints imposed by density regulation may have largely restrained the housing supply and contributed to the increases in home prices in these large cities. As noted by Hilber and Schoni (2016), policymakers should be cautious when implementing demand-side housing policies, especially in areas with severe supply constraints.

Acknowledgements

We would like to thank all seminar participants at the 2016 International Workshop on Regional, Urban, and Spatial Economics in China, the 2016 Meetings of the Global Chinese Real Estate Congress, the 2016 Meetings of the Urban Economics Association, and the 2018 CCES Workshop on Urban Economics for helpful comments and suggestions. Zhang gratefully acknowledges support from the Chinese National Science Foundation (Grant#71673010). Zhang gratefully acknowledges the support of a Global Research Program on Spatial Development of Cities, funded by the Multi-Donor Trust Fund on Sustainable Urbanization of the World Bank and supported by the UK Department for International Development. Any remaining errors are our own.

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Table 1: Summary Statistics

Panel A and Panel B

	Mean	S.D.	Obs.
Panel A: Exactly matched sample			
Per unit land price (yuan per sq. m.)	9,877.14	11,743.96	625
Housing value per land unit (yuan per sq. m.)	27,801.12	26,822.64	625
Land share	0.39	0.59	625
Regulatory FAR level	2.36	1.01	625
Land reserve price (100 million yuan)	5.56	13.13	625
Distance to city center (km)	17.41	14.31	625
Panel B: Generally matched sample			
Per unit land price (yuan per sq. m.)	8,358.66	11,180.62	4,184
Housing value per land unit (yuan per sq. m.)	27,500.87	26,871.87	4,184
Land share	0.31	0.35	4,184
Regulatory FAR level	2.56	1.23	4,184
Land reserve price (100 million yuan)	3.90	8.35	4,184
Distance to city center (km)	18.01	15.72	4,184

Notes: The land sale price and reserve price are converted to constant 2012 price levels using each city's hedonic quality-controlled home price CPI as provided by the Hang Lung Center for Real Estate at Tsinghua University.

Table 1: Summary Statistics (cont'd)

Panel C

City	Mean FAR	Median FAR	10th pct. FAR	90th pct. FAR	S.D.	Obs.
Coastal cities						
Beijing	2.14	2.10	1.27	2.87	0.81	318
Dalian	2.16	1.80	1.08	3.54	1.15	249
Guangzhou	2.73	2.50	1.55	3.90	1.28	72
Hangzhou	2.31	2.30	1.50	3.00	0.65	313
Jinan	2.66	2.80	1.18	3.65	0.93	39
Nanjing	1.97	1.83	1.10	3.00	0.74	204
Ningbo	2.01	2.00	1.30	2.80	0.63	109
Qingdao	2.32	2.00	1.20	4.00	1.17	200
Shanghai	1.70	1.60	1.00	2.50	0.62	156
Shenzhen	2.69	2.36	1.51	4.11	1.21	47
Tianjin	2.02	1.80	1.10	3.20	0.99	385
Wuxi	2.13	2.00	1.40	3.00	0.80	292
Inland cities						
Changchun	1.93	1.90	1.35	2.60	0.53	30
Changsha	3.11	3.00	1.50	5.00	1.39	215
Chengdu	3.46	3.00	1.80	5.10	1.34	376
Ha'erbin	3.25	3.00	1.68	5.20	1.39	197
Kunming	3.60	3.50	1.60	5.72	1.65	125
Nanchang	2.35	2.20	1.50	3.50	1.05	183
Nanning	3.58	4.00	1.91	5.00	1.08	14
Shenyang	2.45	2.20	1.50	3.50	0.97	200
Shijiazhuang	3.48	3.30	2.50	4.50	1.14	61
Taiyuan	3.14	3.45	1.20	5.40	1.54	84
Wuhan	2.98	2.90	1.60	4.50	1.13	179
Xi'an	4.07	3.73	2.70	6.00	1.35	31
Zhengzhou	3.59	3.00	2.00	5.57	1.42	105

Notes: Panel C of Table 1 reports the mean, median, 10th percentile, and 90th percentile of the regulatory FARs in each city using the generally matched sample.

Table 2: Main Regression Results

Dependent variable: Per unit land price				
	Exactly matched sample		Generally matched sample	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Housing value per land unit	0.497***	0.526***	0.316***	0.509***
	(0.100)	(0.116)	(0.074)	(0.076)
Housing value per land unit*log FAR	-0.072	-0.095	-0.011	-0.124***
	(0.065)	(0.058)	(0.036)	(0.034)
Housing value per land unit*log distance to city center	-0.062**	-0.051***	-0.051***	-0.035***
	(0.022)	(0.011)	(0.011)	(0.007)
Housing value per land unit*log reserve price	0.024**	0.030***	0.043***	0.039***
	(0.009)	(0.006)	(0.004)	(0.003)
Housing value per land unit*natural attributes	Yes	Yes	Yes	Yes
Land transaction year dummies	Yes	Yes	Yes	Yes
Land transaction quarter dummies	Yes	Yes	Yes	Yes
City-specific year trends	Yes	Yes	Yes	Yes
Observations	625	625	4,184	4,184
R-squared	0.835	0.832	0.783	0.763
First stage F		4.367		10.81

Notes: *** p<0.01, ** p<0.05, * p<0.1 Heteroskedasticity-robust standard errors (in parentheses) are clustered by the land's transaction year. The city-level natural attributes include the maximum temperature, minimum humidity, roughness of the land surface, and range of land elevation. All of the natural variables have been standardized to have means of zero and standard deviations of one. The excluded instruments include the predicted housing value per land unit and its interactions with the land's regulatory FAR (log and level), the log of the land's distance to the city center, the log of the land's reserve price, and the city-level natural attributes.

Table 3: Regressions with the Less-likely Binding Subsamples

Dependent variable: Per unit land price	Full sample	Bottom 90% subsample	Bottom 80% subsample	Bottom 70% subsample	Bottom 60% subsample	Bottom 50% subsample	Bottom 40% subsample	Bottom 30% subsample	Bottom 20% subsample	Bottom 10% subsample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Housing value per land unit	0.509***	0.531***	0.525***	0.533***	0.528***	0.531***	0.530***	0.523***	0.352**	0.081
	(0.076)	(0.079)	(0.079)	(0.080)	(0.080)	(0.076)	(0.078)	(0.109)	(0.147)	(0.093)
Housing value per land unit*log FAR	-0.124***	-0.131***	-0.130***	-0.132***	-0.129***	-0.133***	-0.136***	-0.114**	-0.026	0.091
	(0.034)	(0.039)	(0.038)	(0.042)	(0.039)	(0.036)	(0.041)	(0.054)	(0.076)	(0.061)
Housing value per land unit*log distance to city center	-0.035***	-0.041***	-0.035***	-0.040***	-0.041***	-0.041***	-0.041***	-0.056***	-0.057***	-0.052**
	(0.007)	(0.006)	(0.007)	(0.006)	(0.010)	(0.012)	(0.011)	(0.013)	(0.014)	(0.026)
Housing value per land unit*log reserve price	0.039***	0.042***	0.039***	0.040***	0.042***	0.038***	0.038***	0.043***	0.054***	0.048***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.004)	(0.007)
Housing value per land unit*natural attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land transaction year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land transaction quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-specific year trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,184	3,766	3,348	2,929	2,511	2,092	1,674	1,256	837	419
R-squared	0.763	0.756	0.743	0.762	0.767	0.733	0.721	0.707	0.747	0.755
First stage F	10.81	11.61	13.25	13.31	15.57	20.81	14.39	15.14	13.15	5.589

Notes: See Table 2 for notes.

Table 4: Robustness Checks

Dependent variable: Per unit land price	Exclude non-binding cases	Within 15km ring around city center	Control for non-competitive sale dummy	Control for two-stage auction dummy	Spatial matching with 0.5 km ring	Bootstrap inference
	(1)	(2)	(3)	(4)	(5)	(6)
Housing value per land unit	0.513***	0.523***	0.472***	0.505***	0.508***	0.509***
	(0.067)	(0.106)	(0.064)	(0.075)	(0.106)	(0.049)
Housing value per land unit*log FAR	-0.122***	-0.128***	-0.105***	-0.121***	-0.132**	-0.124***
	(0.039)	(0.046)	(0.027)	(0.034)	(0.053)	(0.029)
Housing value per land unit*log distance to city center	-0.029**	-0.039***	-0.032***	-0.035***	-0.025**	-0.035***
	(0.012)	(0.009)	(0.008)	(0.007)	(0.010)	(0.010)
Housing value per land unit*log reserve price	0.044***	0.039***	0.040***	0.039***	0.036***	0.039***
	(0.008)	(0.004)	(0.003)	(0.003)	(0.007)	(0.005)
Housing value per land unit*natural attributes	Y	Y	Y	Y	Y	Y
Land transaction year dummies	Y	Y	Y	Y	Y	Y
Land transaction quarter dummies	Y	Y	Y	Y	Y	Y
City-specific year trends	Y	Y	Y	Y	Y	Y
Observations	3,407	2,363	4,184	4,184	1,769	4,184
R-squared	0.772	0.773	0.780	0.764	0.790	0.763
First stage F	7.900	27.07	10.77	11.11	22.25	128

Notes: See Table 2 for notes. Standard errors reported in column (6) are generated on the basis of 1000 bootstrap replications.

Table 5: Effect of Regulatory FAR on Land Share, the Land-Pair Sample

Dependent variable: Ratio of per unit land price to housing value per land unit						
	Full land-pair sample			Exclude pairs with top sale prices		
	500m or less	400m or less	300m or less	500m or less	400m or less	300m or less
	(1)	(2)	(3)	(4)	(5)	(6)
Log regulatory FAR	-0.129***	-0.134***	-0.093***	-0.135***	-0.146***	-0.096***
	(0.028)	(0.032)	(0.027)	(0.034)	(0.041)	(0.024)
Constant	0.407***	0.409***	0.358***	0.371***	0.379***	0.322***
	(0.024)	(0.027)	(0.023)	(0.027)	(0.033)	(0.019)
Pair fixed effects	Y	Y	Y	Y	Y	Y
Number of pairs	567	482	366	387	326	252
Observations	1,134	964	732	774	652	504
R-squared	0.949	0.958	0.916	0.964	0.974	0.933

Notes: *** p<0.01, ** p<0.05, * p<0.1 Heteroskedasticity-robust standard errors are in parentheses. Based on the geographic coordinates of land parcels from the generally matched sample, we match each land parcel with its nearest land parcel and drop the duplicates of land pairs. In columns 1-3, the regression samples are restricted to those pairs with pairwise distances being 500 meters or less, 400 meters or less, and 300 meters or less and sold in the same year, respectively. In columns 4-6, we further exclude the land pairs with at least one land parcel that is in the top quarter of sale prices in each city in each year.

Table 6: FAR Regulation Stringency and Land Characteristics

Dependent variables:	Estimated land share			Regulatory FAR		
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy: subway stop within 2 km		-0.006**	-0.005**		0.162***	0.145**
		(0.003)	(0.003)		(0.057)	(0.057)
Dummy: combined residential and commercial use	-0.021***	-0.019***	-0.020***	0.477***	0.464***	0.485***
	(0.001)	(0.002)	(0.002)	(0.031)	(0.055)	(0.055)
Log land lot size	0.033***	0.025***	0.023***	-0.698***	-0.506***	-0.477***
	(0.001)	(0.002)	(0.002)	(0.030)	(0.045)	(0.044)
Log land distance to city center	-0.035***	-0.029***	-0.025***	-0.021	-0.119**	-0.186***
	(0.001)	(0.002)	(0.002)	(0.027)	(0.049)	(0.047)
Log Land reserve price	0.013***	0.017***	0.019***	0.541***	0.434***	0.402***
	(0.001)	(0.002)	(0.002)	(0.026)	(0.041)	(0.040)
Log prefecture's population size in 2000			0.047**			-0.748**
			(0.019)			(0.356)
Log prefecture's land area			-0.012			0.222
			(0.011)			(0.244)
Land transaction year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Land transaction quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
City-specific year trends	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	No	Yes	Yes	No
Observations	4,184	1,373	1,373	4,184	1,373	1,373
R-squared	0.759	0.732	0.724	0.473	0.485	0.475

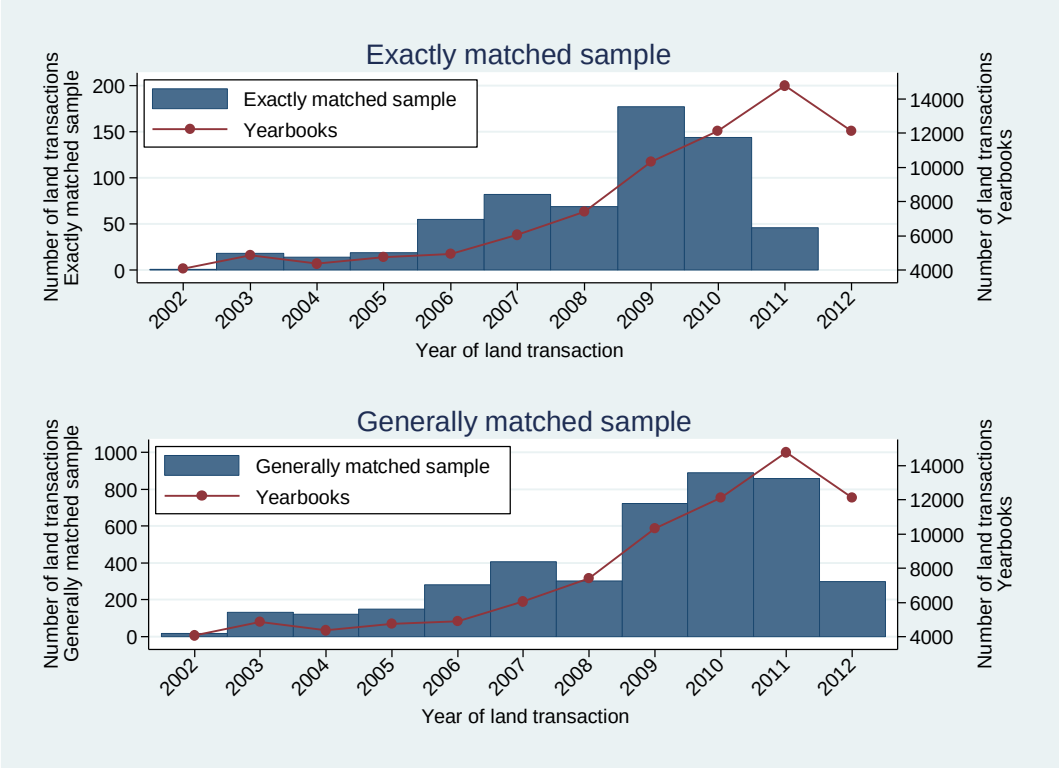
Notes: *** p<0.01, ** p<0.05, * p<0.1 Heteroskedasticity-robust standard errors are in parentheses.

Table 7: FAR Regulation and Housing Price Appreciation

Dependent variable: City's annual growth rate of hedonic house price			
	(1)	(2)	(3)
Annual bank loan growth rate	0.042	-0.432	0.243*
	(0.085)	(0.282)	(0.143)
Annual bank loan growth rate* city's estimated average land share		1.375*	
		(0.739)	
Annual bank loan growth rate* city's average FAR			-0.074*
			(0.042)
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	75	75	75
R-squared	0.749	0.768	0.765

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Each regression is weighted by the total area of transacted land parcels in each city in the generally matched sample.

Figure 1: Land Transaction Volumes over Time

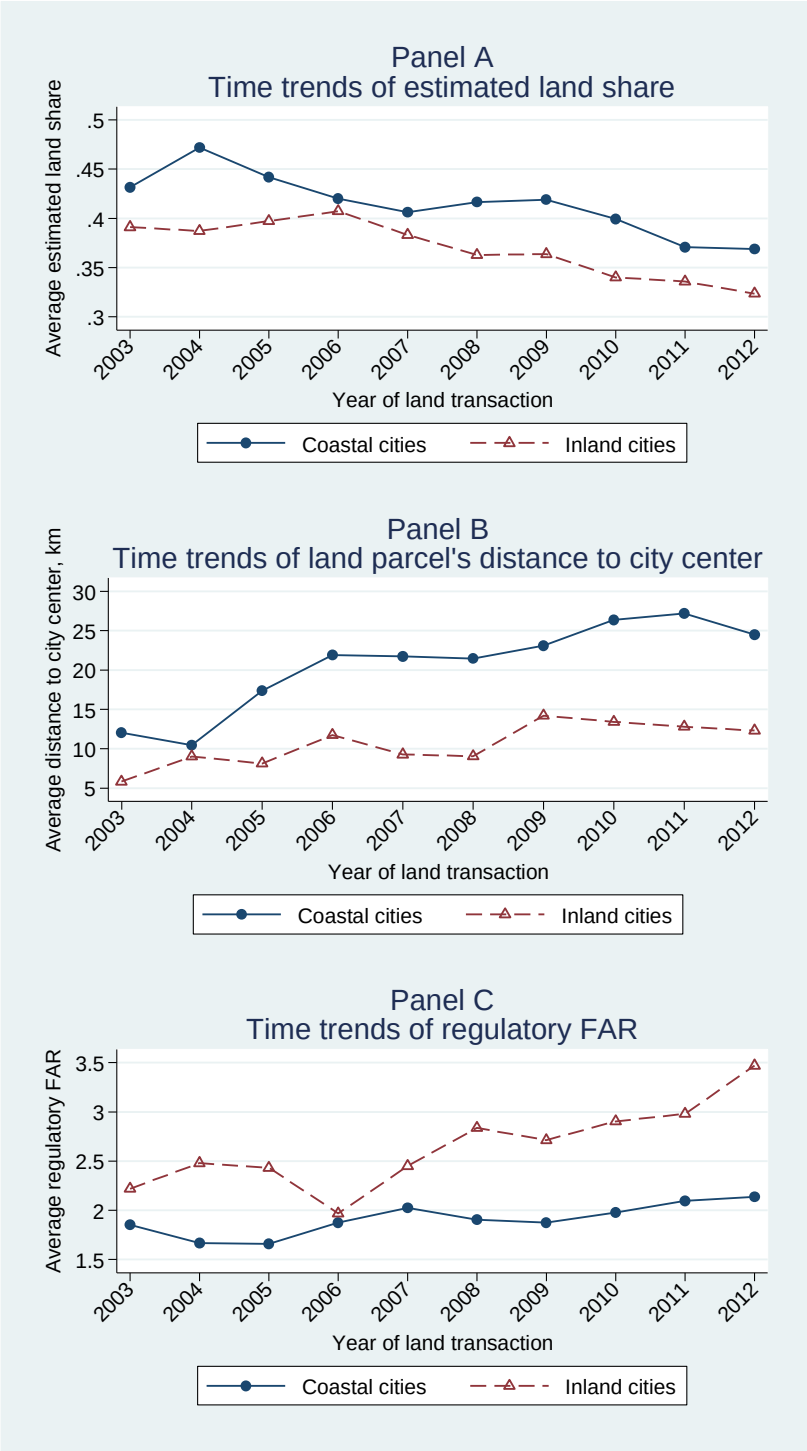


Notes: The graph plots the transaction volumes over time for the exactly and generally matched samples (corresponding to the left y axis in the upper and lower panel, respectively), and the total number of land parcels sold through public auctions for the 25 cities in our sample from the *Yearbooks of Land Resource* (corresponding to the right y axis in each panel).

Figure 2: Regulatory FAR and Distance from City Center

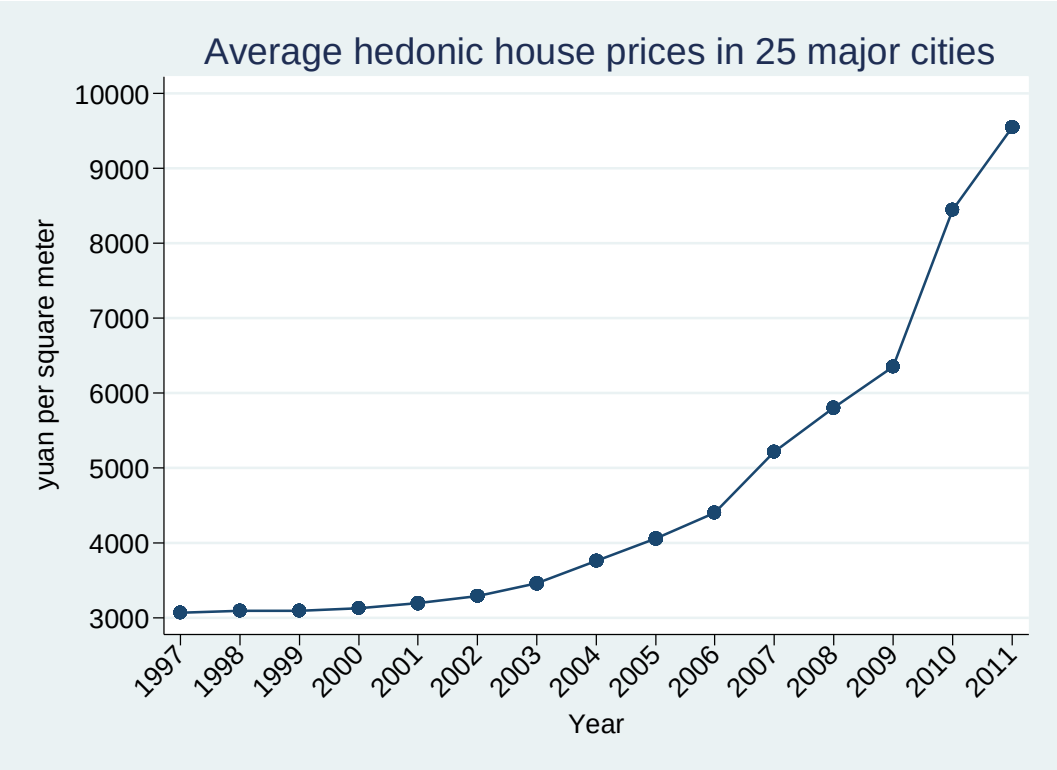
Notes: The curve in each chart is drawn based on the estimation of nonparametric regressions that use a uniform kernel density regression smoother using observations from the generally matched sample.

Figure 3: Trends of Regulation Stringency, Distance to City Center and Regulatory FAR by Region



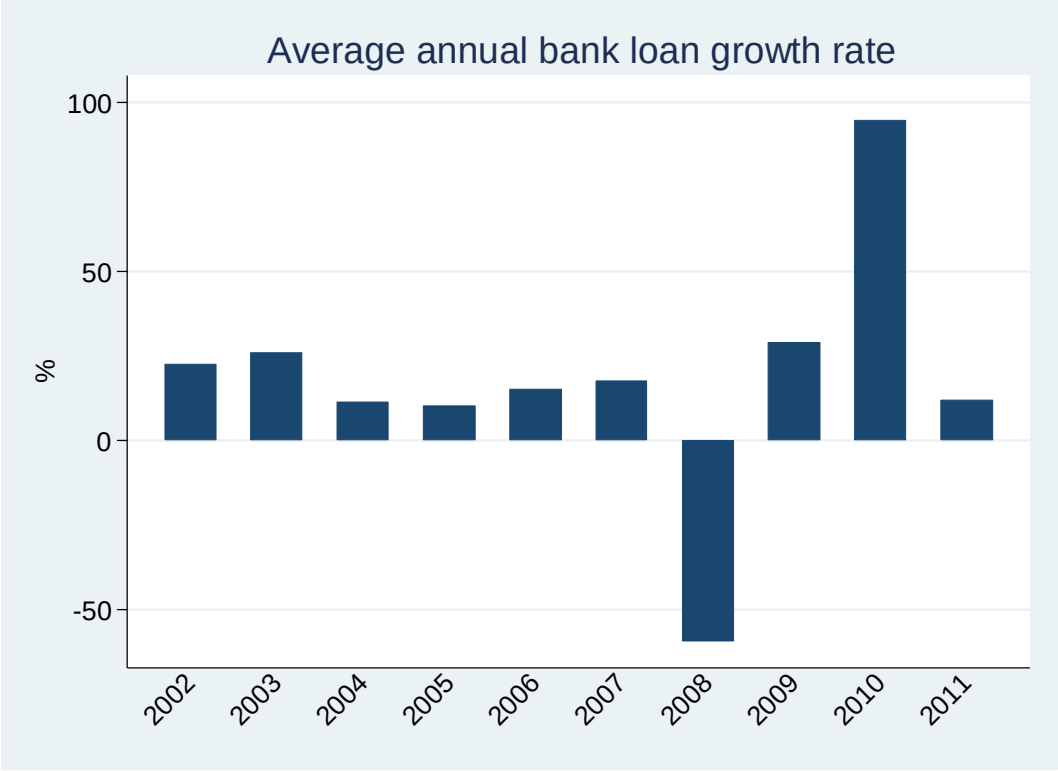
Notes: The graphs are drawn based on the generally matched sample.

Figure 4: Trends of Average Hedonic House Prices in 25 Major Cities



Notes: Figure 4 shows the trends of the hedonic quality-controlled home price index of the 25 cities in our sample. The hedonic house price data are obtained from the Hang Lung Center for Real Estate at Tsinghua University.

Figure 5: Trends of Average Annual Growth Rate of Bank Loans in 25 Major Cities



Notes: The bank loan data are obtained from the *City Statistical Yearbooks 2002-2012*.

Appendices

Appendix A. The equilibrium relationship between per unit land price and housing value per land unit

Let the price of a housing unit be p_h, the price of the quality input M be p_m, and the price of the quantity input F be p_f.

The unconstrained equilibrium

In the case where the quantity restriction is not binding the use of the quantity input, the profit function is

$$\pi^* = p_h A\left(m^{\gamma} f^{1-\gamma}\right)^{1-\beta} - p_m m - p_f f - p_l . \tag{A.1}$$

The first-order conditions are:

$$\frac{\partial \pi^*}{\partial m} = p_h A f^{(1-\gamma)(1-\beta)} m^{\gamma(1-\beta)-1} \gamma(1-\beta) - p_m = 0 \tag{A.2}$$

$$\frac{\partial \pi^*}{\partial f} = p_h A f^{(1-\gamma)(1-\beta)-1} m^{\gamma(1-\beta)} (1-\gamma)(1-\beta) - p_f = 0 \tag{A.3}$$

Eq. (A.2) and (A.3) give the relationship between the unconstrained levels of m and f:

$$f^* = \frac{p_m}{p_f} \frac{1-\gamma}{\gamma} m^* \tag{A.4}$$

Plugging (A.4) into (A.2), we have the unconstrained levels of m and f:

$$m^* = \left(\frac{p_h A\gamma(1-\beta)}{p_m}\right)^{\frac{1}{\beta}} \left(\frac{p_m(1-\gamma)}{p_f \gamma}\right)^{\frac{(1-\gamma)(1-\beta)}{\beta}} \tag{A.5}$$

$$f^* = \left(\frac{p_h A(1-\gamma)(1-\beta)}{p_f}\right)^{\frac{1}{\beta}} \left(\frac{p_f \gamma}{p_m(1-\gamma)}\right)^{\frac{\gamma(1-\beta)}{\beta}} \tag{A.6}$$

The zero-profit condition implies that

$$p_l = v^* - (p_m m^* + p_f f^*) \tag{A.7}$$

where v^* is the housing value per land unit.

Plugging (A.4) into the first term on the right-hand side of (A.7), we have

$$v^* = p_h A\left((m^*)^\gamma (f^*)^{1-\gamma}\right)^{1-\beta} = p_h A(\frac{p_m(1-\gamma)}{p_f \gamma})^{1-\beta}(m^*)^{1-\beta} \tag{A.8}$$

Plugging (A.4) and (A.5) into the second term on the right-hand side of (A.7), we have

$$p_m m^* + p_f f^* = (1-\beta)v^* . \tag{A.9}$$

The proof of (A.9) is:

Plug (A.4) into the second term on the right hand side of (A.7), we have

$$p_m m^* + p_f f^* = p_m m^* + p_f \frac{p_m}{p_f}\frac{1-\gamma}{\gamma} m^* = \frac{1}{\gamma} p_m m^*$$

$$= p_h A(\frac{p_m(1-\gamma)}{p_f \gamma})^{1-\beta}(m^*)^{1-\beta} \frac{p_m m^* / \gamma}{p_h A(\frac{p_m(1-\gamma)}{p_f \gamma})^{1-\beta}(m^*)^{1-\beta}}$$

$$= v^* \frac{1}{\gamma} p_m (p_h A)^{-1}(\frac{p_m(1-\gamma)}{p_f \gamma})^{-(1-\gamma)(1-\beta)}(m^*)^{\beta} \quad \text{(by A.8)}$$

$$= v^* \frac{1}{\gamma} p_m (p_h A)^{-1}(\frac{p_m(1-\gamma)}{p_f \gamma})^{-(1-\gamma)(1-\beta)}((\frac{p_h A\gamma(1-\beta)}{p_m})^{\frac{1}{\beta}}(\frac{p_m(1-\gamma)}{p_f \gamma})^{\frac{(1-\gamma)(1-\beta)}{\beta}})^{\beta} \quad \text{(by A.5)}$$

$$=(1-\beta)v^*$$

QED.

Eq. (A.7) and (A.9) then give the relationship between p_l and v^* in the unconstrained equilibrium:

$$p_l = \beta v^* . \tag{A.10}$$

The constrained equilibrium

In the case where the quantity restriction is binding the use of the quantity input, the profit function is

$$\pi^c = p_h A\left(m^\gamma \overline{f}^{1-\gamma}\right)^{1-\beta} - p_m m - p_f \overline{f} - p_l \tag{A.11}$$

The first-order condition gives the constrained level of m (the use of f is bounded by $\overline{f}$):

$$m^c = \left(\frac{p_h A(1-\beta)\gamma}{p_m}\right)^{\frac{1}{\beta+(1-\gamma)(1-\beta)}} \overline{f}^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}} \tag{A.12}$$

Let

$$\chi_f \equiv \frac{f^*}{\overline{f}}, \tag{A.13}$$

where $\chi_f > 1$ in the case where $\overline{f}$ is binding the use of f.

Let

$$\chi_m \equiv \frac{m^*}{m^c}. \tag{A.14}$$

From (A.14), (A.4) and (A.12), we have

$$\chi_m = \chi_f^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}}. \tag{A.15}$$

The proof of (A.15) is:

$$\begin{aligned}
\chi_m &= \frac{m^*}{m^c} \\
&= \frac{\frac{p_f \gamma}{p_m(1-\gamma)} f^*}{m^c} && \text{(by A.4)} \\
&= \frac{\frac{p_f \gamma}{p_m(1-\gamma)} f^{*1-\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}} f^{*\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}}}{\left(\frac{p_h A(1-\beta)\gamma}{p_m}\right)^{\frac{1}{\beta+(1-\gamma)(1-\beta)}} \overline{f}^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}}} && \text{(by A.12)}. \\
&= \left(\frac{f^*}{\overline{f}}\right)^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}} && \text{(by A.6)} \\
&= \chi_f^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}}
\end{aligned}$$

QED.

The unconstrained housing supply per land unit is

$$h^* = A(m^{*\gamma} f^{*1-\gamma})^{1-\beta}. \tag{A.16}$$

The constrained housing supply per land unit is

$$h^c = A((m^c)^\gamma \overline{f}^{1-\gamma})^{1-\beta}. \tag{A.17}$$

The stringency of FAR regulation on housing supply per land unit is

$$\chi \equiv \frac{h^*}{h^c} = \chi_m = \chi_f^{\frac{(1-\gamma)(1-\beta)}{\beta+(1-\gamma)(1-\beta)}}. \tag{A. 18}$$

Proof:

$$h^c = A((m^c)^\gamma \overline{f}^{1-\gamma})^{1-\beta} = A[(\frac{m^*}{\chi_m})^\gamma (\frac{f^*}{\chi_f})^{1-\gamma}]^{1-\beta} \quad \text{(by A.13 and A.14)}$$
$$= A(m^{*\gamma} f^{*1-\gamma})^{1-\beta} \chi_m^{-\gamma(1-\beta)} \chi_f^{-(1-\gamma)(1-\beta)}$$
$$= h^* \chi_m^{-1} \quad \text{(by A.15)}$$

QED.

The unconstrained housing value per land unit is $v^* = p_h h^*$, and the constrained housing value per land unit is $v^c = p_h h^c$. By (A.18), we have

$$v^c = v^* \chi_m^{-1} = v^* \chi^{-1}. \tag{A. 19}$$

Zero-profit condition, (A.13), (A.14), (A.15), (A.18), and (A.19) give the relationship between p_l and v^c in the constrained equilibrium:

$$p_l = \tilde{\beta} v^c, \tag{A.20}$$

where $\tilde{\beta} \equiv \beta + (1-\gamma)(1-\beta)(1-\chi^{\frac{-\beta}{(1-\gamma)(1-\beta)}})$.

Proof:

$$p_l = p_h A[(m^c)^\gamma (\overline{f})^{1-\gamma}]^{1-\beta} - p_m m^c - p_f \overline{f} \qquad \text{(zero-profit condition)}$$

$$= p_h A[(\frac{m^*}{\chi_m})^\gamma (\frac{f^*}{\chi_f})^{1-\gamma}]^{1-\beta} - p_m \frac{m^*}{\chi_m} - p_f \frac{f^*}{\chi_f} \qquad \text{(by A.13 and A.14)}$$

$$= p_h A(m^{*\gamma} f^{*1-\gamma})^{1-\beta} \chi_m^{-\gamma(1-\beta)} \chi_f^{-(1-\gamma)(1-\beta)} - (p_m m^* \chi_m^{-1} + p_f f^* \chi_f^{-1})$$

$$= v^* \chi_m^{-1} - (1-\beta) v^* (\gamma \chi_m^{-1} + (1-\gamma)\chi_f^{-1}) \qquad \text{(see proof details below)}$$

$$= v^* \chi_m^{-1} [1 - (1-\beta)\gamma - (1-\beta)(1-\gamma)\frac{\chi_m}{\chi_f}]$$

$$= v^* \chi_m^{-1} [\beta + (1-\beta)(1-\gamma)(1-\frac{\chi_m}{\chi_f})]$$

$$= v^c [\beta + (1-\beta)(1-\gamma)(1-\frac{\chi_m}{\chi_f})] \qquad \text{(by A.19)}$$

$$= v^c [\beta + (1-\beta)(1-\gamma)(1-\chi_f^{-\frac{\beta}{\beta+(1-\gamma)(1-\beta)}})] \qquad \text{(by A.15)}$$

$$= v^c [\beta + (1-\beta)(1-\gamma)(1-\chi^{-\frac{\beta}{(1-\gamma)(1-\beta)}})] \qquad \text{(by A.18)}$$

The details of the proof:

$$p_h A(m^{*\gamma} f^{*1-\gamma})^{1-\beta} \chi_m^{-\gamma(1-\beta)} \chi_f^{-(1-\gamma)(1-\beta)}$$
$$= v^* \chi_m^{-\gamma(1-\beta)} \chi_f^{-(1-\gamma)(1-\beta)}$$
$$= v^* \chi_m^{-1} \qquad \text{(by A.15)}$$

$$p_m m^* \chi_m^{-1} + p_f f^* \chi_f^{-1} =$$
$$p_m m^* \chi_m^{-1} + p_m \frac{1-\gamma}{\gamma} m^* \chi_f^{-1} \qquad \text{(by A.4)}$$
$$= p_m m^* (\chi_m^{-1} + \frac{1-\gamma}{\gamma} \chi_f^{-1})$$
$$= \frac{1}{\gamma} p_m m^* (\gamma \chi_m^{-1} + (1-\gamma)\chi_f^{-1})$$
$$= (1-\beta) v^* (\gamma \chi_m^{-1} + (1-\gamma)\chi_f^{-1}) \qquad \text{(by the proof of A.9)}$$

QED.

Appendix B. The aggregate housing supply equation.

From (A.5), (A.6), (A.16), and (A.18), the constrained housing supply per land unit can be written as a function of three price variables:

$$h^c = \psi p_h^{\frac{1-\beta}{\beta}} p_m^{-\frac{\gamma(1-\beta)}{\beta}} p_f^{-\frac{(1-\gamma)(1-\beta)}{\beta}} \chi^{-1} \tag{A.21}$$

where $\psi \equiv A^{\frac{1}{\beta}} (1-\beta)^{\frac{1-\beta}{\beta}} \gamma^{\frac{\gamma(1-\beta)}{\beta}} (1-\gamma)^{\frac{(1-\gamma)(1-\beta)}{\beta}}$.

Proof:

$$\begin{aligned} h^c &= h^* \chi^{-1} \\ &= A(m^{*\gamma} f^{*1-\gamma})^{1-\beta} \chi^{-1} \\ &= A^{\frac{1}{\beta}} (1-\beta)^{\frac{1-\beta}{\beta}} \gamma^{\frac{\gamma(1-\beta)}{\beta}} (1-\gamma)^{\frac{(1-\gamma)(1-\beta)}{\beta}} p_h^{\frac{1-\beta}{\beta}} p_m^{-\frac{\gamma(1-\beta)}{\beta}} p_f^{-\frac{(1-\gamma)(1-\beta)}{\beta}} \chi^{-1} \quad \text{(by A.5 and A.6)} \end{aligned}$$

QED.

The aggregate housing supply equation is:

$$H^S = \sum h_i L_i \tag{A.22}$$

where L_i represents the total land used by developer i.

Plugging (A. 21) into (A. 22), we rewrite the aggregate housing supply equation as

$$H^S = \psi p_h^{\frac{1-\beta}{\beta}} p_m^{-\frac{\gamma(1-\beta)}{\beta}} p_f^{-\frac{(1-\gamma)(1-\beta)}{\beta}} \chi^{-1} \bar{L} \tag{A.23}$$

where $\sum L_i \equiv \bar{L}$, and $\psi \equiv A^{\frac{1}{\beta}} (1-\beta)^{\frac{1-\beta}{\beta}} \gamma^{\frac{\gamma(1-\beta)}{\beta}} (1-\gamma)^{\frac{(1-\gamma)(1-\beta)}{\beta}}$. As shown by (A.23), the housing supply elasticity respect to house price is $(1-\beta)/\beta$.

Appendix C. A model extension: Adopting a new housing technology

Suppose all the developers use the current technology and reach the constrained equilibrium with zero profit. Suppose that an alternative technology with higher land share $\beta_A > \beta$ becomes available in the housing production function. Under the new technology, the use of the quantity input is no longer bounded by regulation.[33]

The potential gain from adopting the new technology is given by

$$\pi_A = \beta_A v_A^* - \overline{p}_l - c$$
$$= \beta_A v_A^* - \left[\left(1-\gamma+\gamma\beta\right)\chi^{-1} - \left(1-\beta\right)\left(1-\gamma\right)\chi^{\frac{-(1-\gamma+\gamma\beta)}{(1-\beta)(1-\gamma)}} \right] v^* - c \quad \text{(by A.19 and A.20)}$$

where $v_A^* \equiv p_h A[(m_A^*)^\gamma (f_A^*)^{1-\gamma}]^{1-\beta_A}$, which is the optimal housing value per unit of land with the new technology, $v^* \equiv p_h A[(m^*)^\gamma (f^*)^{1-\gamma}]^{1-\beta}$, which is the optimal housing value per unit of land with the old technology, $\overline{p}_l$ represents the initial per-unit land price, and c represents the fixed adjustment cost.

Taking the partial derivative of π_A with respect to χ, we have

$$\frac{\partial \pi_A}{\partial \chi} = \left(1-\gamma+\gamma\beta\right)\left(\chi^{-2} - \chi^{-2-\frac{\beta}{(1-\gamma)(1-\beta)}} \right) v^* > 0, \quad \chi > 1.$$

Therefore, the potential gains from switching increase with the stringency of constraints such that when the constraints are strong enough, the gains exceed the switching cost and the developer switches to the new technology.

QED.

[33] From (A.6), we know that the optimal level of the quantity input, f^*, is decreasing in β.

Appendix D: Supplementary Tables and Figures

Table A1: Per-floor-area RDP Price and Locational Attributes

Dependent variable: Per-floor-area RDP price, yuan per sq. m.		
	Exactly matched sample	Generally matched sample
	(1)	(2)
Log distance to city center	-4,154.553***	-4,056.078***
	(430.122)	(183.975)
City fixed effects	Y	Y
Observations	625	4,184
R-squared	0.444	0.456

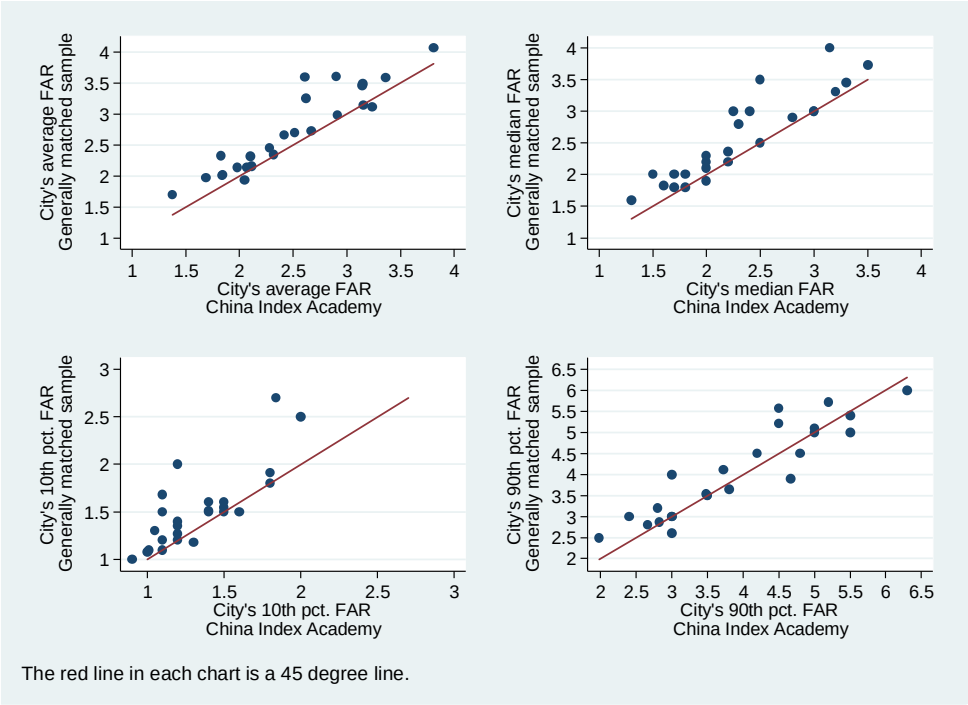
Notes: *** p<0.01, ** p<0.05, * p<0.1 Heteroskedasticity-robust standard errors are in parentheses.

Table A2: Correlations between Regulatory FAR and Observed Locational Characteristics

	Log distance to city center			Log distance to nearest government building			Log distance to nearest subway station			Log lot size		
	<=500m	<=400m	<=300m	<=500m	<=400m	<=300m	<=500m	<=400m	<=300m	<=500m	<=400m	<=300m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log regulatory FAR	0.007	0.001	0.001	-0.008	0.002	0.017	0.043	0.033	0.006	-0.065	-0.069	-0.178
	(0.007)	(0.005)	(0.003)	(0.028)	(0.029)	(0.023)	(0.030)	(0.036)	(0.012)	(0.165)	(0.184)	(0.236)
Pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of pairs	567	482	366	567	482	366	172	145	106	567	482	366
Observations	1,134	964	732	1,134	964	732	344	290	212	1,134	964	732
R-squared	0.999	1.000	1.000	0.995	0.996	0.996	0.997	0.998	0.999	0.790	0.797	0.798

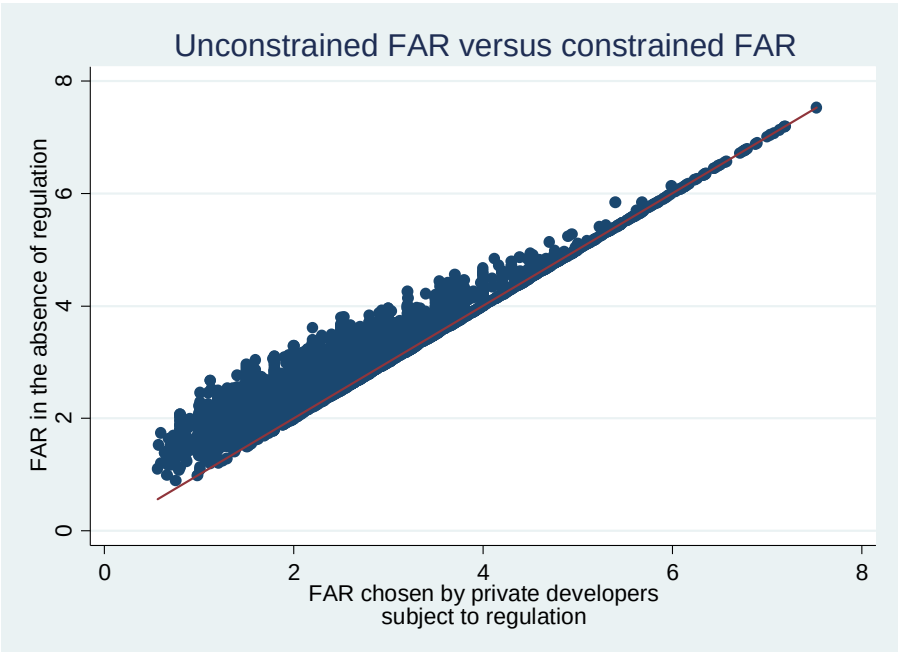
Notes: See Table 5 for notes.

Figure A1: Sample Representativeness



Notes: The FAR percentile of each city on the y axis is calculated from the generally matched sample, and that on the x axis is calculated from the land transaction data provided by the China Index Academy which covers all residential land transactions that occurred through public auctions from 2000 through 2011.

Figure A2: Unconstrained and Constrained FARs



Notes: We borrow the estimates from Cai, Wang and Zhang (2017) to calculate the unconstrained FARs that would maximize land value in the absence of regulation, and plot these levels against the predicted FARs chosen by the developers (constrained FARs) in the graph above for the generally matched sample.