# Land (Mis)allocation and Local Public Finance in China*

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**Abstract**

Government intervention in China's land markets raises concerns about land misallocation. The 10-fold price premium for residential over industrial land is often viewed as evidence of significant misallocation. We show this argument is misleading—industrial land generates long-run tax payment whereas residential land does not. Accounting for tax differences, firms pay slightly less for industrial than residential land, indicating a modest oversupply of industrial land nationwide. Cross-sectionally, industrial land is oversupplied in developed areas but undersupplied elsewhere. Tax incentives affect local governments' land allocation: industrial land supply increases with their retained share of tax and decreases with their borrowing cost.

**Keywords**: Misallocation, Municipal Finance, Municipal Corporate Bonds, Tax, Cost of Capital

**JEL classifications**: H70, G31, R14, R38

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# 1 Introduction

The misallocation of resources is a central question in economics. As a key input factor in any economy, misallocation of land resources can lead to significant distortions in productivity and welfare losses. In China, the land market and municipal finances are intertwined: local governments intermediate most land supply in their jurisdiction, enjoying both direct land sales and associated tax revenues. Government intervention in the land market raises concerns about land misallocation in China.

Notably, during 2007–19, Chinese local governments sold residential land for prices about ten times more than industrial land. Many view this large price disparity as evidence of significant land misallocation and conclude residential land is sold primarily to raise revenue, whereas industrial land is sold primarily for nonpecuniary reasons (e.g., subsidizing industry, supporting labor demand). As noted by Liu and Xiong (2020, 193), "it is a common practice for local governments throughout China to offer industrial land at subsidized prices to support local industries."[1]

This conventional view overlooks a key issue: residential and industrial land in China have different tax profiles. Industrial land generates a permanent flow of tax payments after land acquisition, as firms continue production on the land. In contrast, residential land only yields temporary tax payments from home development, as there is no residential property tax in China. In any competitive market equilibrium, the marginal output of land equals the sum of the present value of all marginal tax payment and the upfront land price; the competitive equilibrium is Pareto efficient if and only if the above sum is the same for residential and industrial land. With more future taxes on industrial and more upfront payment on residential land, it is ambiguous whether such land allocation efficiency condition holds and if not, which type of land is oversupplied.

By quantifying the tax payments, we find little evidence supporting the view that industrial land is "subsidized." Firms' average total payments for industrial land were only slightly less than those for residential land during 2007–10, suggesting a modest oversupply of industrial land relative to the Pareto-efficient level. While nearly half of Chinese cities achieve near-efficient allocation, we document notable regional heterogeneity. Developed areas with higher house prices have a relative undersupply of residential land and oversupply of industrial land; the opposite

[1] A broad narrative holds China "favor[s] industry and investment over the service sector and domestic consumption"; recently, China shifted to target subsidies at specific "strategic" industrial sectors (Liu, 2019).

holds in less developed areas. To identify supply-side factors driving the spatial variation, we find suggestive causal evidence that tax incentives affect local governments' zoning decisions: when local governments face higher borrowing costs or retain smaller shares of future industrial tax revenues, they sell more residential and less industrial land. These results not only confirm tax's importance for understanding land allocation efficiency, but also imply shocks to local government finances have knock-on effects on land allocation and industry structure.

To empirically evaluate the land allocation efficiency condition, we consider the different timing of industrial and residential land tax payments to calculate the implied discount rate (IDR) under which the efficiency condition holds. We can then compare IDR with estimates of discount rates for China's industrial firms. An IDR higher than the economy's discount rate indicates an undersupply of industrial land relative to the Pareto efficient level; a lower IDR indicates the opposite.

To measure IDR, we need to estimate three quantities: average price discount on industrial versus residential land (hereafter, "industrial discount"); long-term tax payment increases from firms that purchase industrial land; and one-time tax payments from residential firms due to home development. We rely on three datasets. The first contains data on the universe of land parcels sold by the government during 2007–19. We observe each parcel's price, zoning, buyer name, location and size. The second contains data on large Chinese industrial firms during 1998–2013. The last is annual financial reports from listed home developers during 2008–21. By merging the first two datasets, we can identify industrial firms that acquired any industrial land during 2007–10, for which we can estimate the consequent effect on its tax payments for at least three years after acquiring land. Our primary estimates of IDR are thus based on land sales during 2007–10.

We estimate the industrial discount under a potential-outcomes framework. Using observed residential (industrial) sale prices to estimate a hedonic model, we predict prices of industrial (residential) land parcels if they were, counterfactually, sold as residential (industrial). The industrial discount is the difference between the actual (predicted) residential and the predicted (actual) industrial price. We measure average industrial discount at the city-year level weighted by land size. During 2007–10, the average industrial land discount is 1794.2 RMB/$m^2$ (88% of the average residential land price).

For marginal tax payment from industrial land, we first adopt the differences-in-differences approach based on propensity score matching (PSM-DID) to estimate the marginal impact of land purchases on firms' sales. We then multiply the increase in sales by an effective tax rate, taking into account the spillover effect on upstream firms. For land purchases during 2007–10 and using firms' sales data before 2013, we find that annual marginal taxes are 71.4 RMB/$m^2$ on average in the first three years, and 183.5 RMB/$m^2$ thereafter. To obtain the long-run increase in tax payment, we assume marginal tax payments grow at the same rate as observed aggregate tax revenues before 2024 and zero afterwards. To accommodate potential spatial heterogeneity in industrial taxes, we allow the marginal impact of land purchase on firm sales to vary with the city's industrial discount and obtain city-level estimates of the industrial tax.

Finally, we estimate the incremental tax payment from home development and home sales at the city-year level, taking into account the spillover effect on upstream suppliers. The average tax from residential land supply during 2007–10 is about 2029 RMB/$m^2$ across different cities.

Given these estimates, we find that national IDR during 2007–10 is 6.3%. We use firms' cost of capital as their discount rates (Berk and DeMarzo, 2017).[2] Using data on listed industrial firms during 2007–10, we estimate the average cost of capital to be 8.0%. The estimated IDR is only slightly lower than firms' discount rate, suggesting modest industrial land oversupply. This key takeaway is robust to checks addressing potential biases to IDR estimates (e.g., government subsidies, alternative cash flow timing).

The national IDR masks notable heterogeneity in land allocation efficiency across cities. At the city level, IDR negatively correlates with local GDP per capita, with 116 out of 204 cities having an IDR below 8.0% and the other 88 above 8.0%. This implies that local governments can improve land allocation efficiency by increasing residential land supply in more developed areas—which tend to experience population inflows and high house prices—while increasing industrial land supply in less developed areas, where housing demand is relatively low. Moreover, the overall magnitude of land misallocation appears modest in many cities: 89 out of the 204 cities have an IDR between 7% and 9%, deviating from firms' discount rates by less than 1%. Over time, the IDR seems to be decreasing and the gap with firms' discount rates widened from 2007 to 2019, suggesting that a reallocation of land supply from industrial to residential can improve welfare, consistent with the fact that house prices have increased significantly over this period.

[2]Following the Modigliani–Miller theorem (Modigliani and Miller, 1958), cost of capital used in calculating present value should be determined by the cash flows' risk profile. As firms' tax payments share similar risk profiles to their free cash flows, cost of capital is an appropriate discount rate for future tax payments.

In the second part of the paper, we investigate supply-side factors that influence local government land allocation decisions. We show that the government's optimal choice of land allocation is efficient if local governments i) fully internalize all tax revenues, ii) are not myopic, iii) do not value any nonpecuniary benefits, iv) have the same discount rate as firms, and v) possess no market power in the land markets. Some deviations from this benchmark would lead to more industrial land supply, such as governments valuing nonpecuniary benefits or exerting market power in the residential land market. Other deviations—including intergovernmental tax sharing, government financial distress, or local official myopia—would lead to the opposite.

In addition to the quantitative importance of industrial tax revenues, we provide suggestive causal evidence that local governments do value industrial tax revenues when making land allocation decisions. We empirically test two hypotheses tied to the tax incentives. The first relates to governments' cost of capital: when local governments are more financially constrained, they should sell more residential land, depressing residential prices and industrial discounts. The second concerns intergovernmental tax sharing: if local governments retain a larger share of tax revenues from industrial land, they will sell more industrial land, increasing industrial discounts.

We find support for both predictions. We show that cross-sectionally, industrial land discounts are negatively associated with local governments' borrowing cost measured by local governments' municipal corporate bond yields; and this negative correlation remains when we instrument municipal corporate bond yields using a political economy–based instrument that builds on Chen et al. (2020). Regarding the second hypothesis on intergovernmental tax sharing, we exploit a policy reform in local-central tax sharing in 2016 and find a positive cross-sectional correlation between industrial land discounts and the proportion of value-added taxes retained by city governments. These results suggest that shocks to local governments' financial conditions can propagate into land markets and generate long-run impacts on local industry structure.

**Literature review.** Our paper is related to the factor misallocation literature. Building on seminal work by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), this literature measures equilibrium misallocation by estimating the cross-sectional dispersion of marginal products and using structural methods to quantify welfare losses from misallocation. Our paper differs in two ways. First, these papers rely on specific production functions to estimate marginal products, a method with well-known limitations including measurement errors and adjustment costs (Asker et al., 2014; Bils et al., 2021), and to compare the marginal products across firms; we instead use firms' marginal payment to proxy for marginal outputs and investigate the variation across sectors (residential and industrial). We abstract from within-sector variations in marginal products across firms because our main interest is cross-sector land allocation efficiency. Second, rather than quantifying welfare losses, our paper sets out to address a conceptual issue when assessing resource misallocation involving differential tax treatment in different sectors.

We show that failing to account for differences in firms' tax payment can lead to misleading conclusions about the extent of land misallocation in China, an issue that has been ignored in the large urban and public finance literature on China. Most existing papers maintain that industrial land is subsidized for local governments' nonpecuniary incentives. For example, Tao et al. (2010) propose that local governments use subsidized industrial land in competition for investment. Huang and Du (2017) view the price disparity between residential and industrial land as evidence of misallocation and discuss government incentives underlying this misallocation. Liu and Xiong (2020) argue the industrial price gap is due to local governments' incentives to subsidize local industries. Zhou et al. (2022) investigate the effect of land misallocation on carbon emissions efficiency and Xie et al. (2022) study the impacts on urban green total factor productivity.

Our paper relates to the literature on local government financing's effects. Many have analyzed how local governments' fiscal conditions and debt-issuing capacities influence their expenditures, other sources of revenues, local policies, and real outcomes. Yi (2021), Posenau (2021), and Agrawal and Kim (2021) show credit-constrained municipalities cut spending, especially infrastructure investment and public facility expenditures, lowering public service quality. Giesecke and Mateen (2022) show local governments respond to negative fiscal shocks from a large decline in property values by raising property tax rates. Adelino et al. (2017) show changes in local governments' financing costs can influence local governments' employment, private sector employment, and income. Zhuravskaya (2000) shows tax sharing between regional and local governments in Russia discourages local governments from increasing the tax base or providing public goods.

This literature has also examined the interaction between local public finance and land regulations, particularly fiscal incentives associated with different land use types (Altshuler and Gomez-Ibanez, 2000; Blöchliger et al., 2017). Quigley and Raphael (2005) contend that tax policies in California create fiscal incentives to favor retail development over housing construction because property taxes are constitutionally limited while cities are permitted a share of local sales tax receipts. Burnes et al. (2014) find that Florida jurisdictions with higher sales tax rates prefer to attract large shopping malls over manufacturing firms through fiscal zoning. Cheshire and Hilber (2008) investigate how in the UK the shift in tax revenues levied on commercial real estate from local authorities to the central government implies fiscal disincentives for commercial development, leading to high office space prices. Our analysis about the effect of government borrowing costs and intergovernmental tax sharing on land zoning aligns with these findings.

The remainder of the paper is organized as follows. We introduce our data in Section 2, lay out the conceptual framework in Section 3, perform the empirical estimation in Section 4, and discuss supply-side factors in Section 5. We conclude in Section 6.

## 2 Institutional Details and Data

This sections explains the institutional background of land supply in China, and provides detailed descriptions of the datasets we use.

### 2.1 Land Allocation in China

Unlike in countries such as the US, where land transactions occur directly between private parties, local governments intermediate most land transactions in China. Specifically, local governments repossess "underutilized" land after compensating existing occupants and then resell the land to market participants using auction-like mechanisms. Both direct land sales and tax revenues generate large profits for local governments. Economically, this process allows local governments to upgrade public infrastructure and encourages building more efficient structures on land.

The central government largely determines the total amount of land supply and local governments have substantial discretion over land zoning. The land usage permitted for each land parcel falls into four categories: residential land for houses and apartments, industrial land for factories and warehouses, commercial land for offices and shopping malls, and public utility land for public facilities. In this study, we focus on residential and industrial land, which accounted for 86% of the total land supply area during 2007-19.

The urban landscape is mostly regulated by two laws: the Land Administration Law and the Urban and Rural Planning Law. These two laws regulate the division between urban and rural land and the spatial layout of urban and rural areas. During our sample period, they were enforced by the "Land Use Overall Plans" at all levels of governments and by the "Urban Overall Plans" at the city and subordinate level. In general, the first set of plans lists regulations about cities' scales, while the second gives more details on land zoning. In drafting these plans, upper-level governments (central and provincial) lay out planning guidelines like caps on city scale, and lower-level governments (city and subordinate county and town) are in charge of specifying land zoning in detail down to the parcel level. Although lower-level plans are always subject to the review of upper-level governments, the choice of zoning for different uses is largely in the hands of local governments, especially in the short run. This non-market-based mechanism for land allocation raises concerns about allocation efficiency.

## 2.2 Data

We now explain the data used in this paper, with summary statistics in Table 1.

**Land sale data.** Land sale data from the Ministry of Natural Resources cover the universe of 2007–19 land sales by Chinese local governments. For each transaction, we observe the land's geographic location, size, transaction date, price, and designated use type. We focus on residential and industrial land parcels allocated by agreement and auction.[3] We retrieve data on land parcels' geographical coordinates using the Gaode maps API, a leading location based services provider in China. Figure 1 shows that residential land prices significantly exceed industrial land prices; the price gap increases over time.

**Firm data.** To estimate industrial land tax payments, we use industrial firm data from the Annual Survey of Industrial Firms (ASIF) administered by the National Bureau of Statistics on all industrial (manufacturing, mining, and utility) firms in China during 1998–2013. For each firm, we observe detailed information (e.g., firm name, industry, annual sales, profits, tax payment). Despite some data quality concerns (Nie et al., 2012), the data are widely used in economic research on China.[4]

To estimate the marginal impact of land acquisition on firm sales, we merge firm data with industrial land purchase data using firm names, taking into account firms buying land through

[3]Throughout the paper, we use "auction" to refer to three types of allocation method – tender, listing, and auction. Agreements are not necessarily market-based transfers, while the three auction methods are. We exclude an allocation mechanism called "administrative allotments" involving no payment from land receivers, which is used for infrastructure, government offices, military facilities, etc.

[4]Some studies use the data until 2005 (Hsieh and Klenow, 2009) or 2007 (Liu and Lu, 2015; Bai et al., 2019), and others use it until 2013 (Heinrich et al., 2020; Cen et al., 2021; Tang et al., 2021). For the year 2010, all operating information except sales and employment is missing, and we drop that year due to concerns about data quality. Besides the issue of missing 2010 data, the data is also subject to censoring and random dropout concerns, which we analyze in the Online Appendix B.5.

Table 1: Data Summary

| | Obs | Mean | Std Dev | P10 | P50 | P90 |
|---|---|---|---|---|---|---|
| ***A. Land characteristics*** | | | | | | |
| ***Residential*** | | | | | | |
| Land Price, RMB/$m^2$ | 292,371 | 2,113.22 | 2,595.73 | 264.40 | 1,200.00 | 5,101.21 |
| Area, 1000 $m^2$ | 292,371 | 29.80 | 46.90 | 0.20 | 15.30 | 69.50 |
| Distance to urban unit centers, km | 292,371 | 9.26 | 11.60 | 0.91 | 5.15 | 22.06 |
| ***Industrial*** | | | | | | |
| Land Price, RMB/$m^2$ | 371,717 | 252.30 | 260.43 | 96.00 | 199.11 | 445.48 |
| Area, 1000 $m^2$ | 371,717 | 36.60 | 73.30 | 3.30 | 17.40 | 80.40 |
| Distance to urban unit centers, km | 371,717 | 10.28 | 10.93 | 1.46 | 7.57 | 21.77 |
| ***B. Firm characteristics*** | | | | | | |
| ***Residential*** | | | | | | |
| Sales, million RMB | 1,729 | 9275.22 | 28673.80 | 443.59 | 2352.02 | 18326.41 |
| Cost, million RMB | 1,729 | 6328.86 | 20170.43 | 281.86 | 1450.66 | 12380.30 |
| OtherTax, million RMB | 1,729 | 737.26 | 2203.76 | 10.15 | 189.44 | 1453.62 |
| IncomeTax, million RMB | 1,729 | 432.19 | 1406.95 | 5.80 | 115.95 | 807.18 |
| ***Industrial*** | | | | | | |
| ***-Treated Firms*** | | | | | | |
| Profit margin | 21,976 | 0.05 | 0.08 | 0.00 | 0.04 | 0.13 |
| Sale, 1000 RMB | 21,752 | 179,459 | 371,021 | 11,457 | 61,288 | 411,539 |
| Area, 1000 $m^2$ | 4,349 | 34.11 | 45.43 | 4.55 | 18.83 | 80.00 |
| ***-Control Firms*** | | | | | | |
| Profit margin | 22,345 | 0.05 | 0.14 | 0.00 | 0.04 | 0.13 |
| Sales, 1000 RMB | 22,110 | 174,007 | 353,169 | 10,815 | 60,484 | 402,751 |
| ***C. City characteristics*** | | | | | | |
| IndDisc, RMB/$m^2$ | 3,092 | 1,520.86 | 1,416.96 | 223.86 | 1,082.47 | 3,472.72 |
| City VAT Share, % | 2,839 | 23.94 | 10.15 | 15.00 | 20.00 | 40.00 |
| Change of Ctiy VAT Share in 2016, % | 216 | 20.29 | 6.41 | 16.25 | 20.00 | 27.50 |
| City MCB Coupon rate, % | 257 | 6.96 | 0.80 | 5.88 | 6.98 | 8.00 |
| Deficit/GDP | 257 | 0.09 | 0.08 | 0.01 | 0.07 | 0.17 |
| GDP growth rate, % | 257 | 13.39 | 3.19 | 10.10 | 13.20 | 16.50 |
| GDP per capita, 10,000 RMB | 257 | 2.46 | 1.71 | 0.97 | 1.93 | 4.98 |
| LateTerm | 257 | 0.14 | 0.35 | 0.00 | 0.00 | 1.00 |

Note: This table reports summary statistics at the land, firm-year and city-year levels. Panel A is based on the residential and industrial land auction transactions during 2007–19; Panel B is based on the listed developers and the matched sample of firms used to estimate the effect of land purchase on sales. In Panel C, the first two variables are time-varying city characteristics during 2007–19, the next four variables are city-level characteristics in 2008, and the last is a binary indicator for whether the provincial governor had been in office for more than three years at the end of 2008.

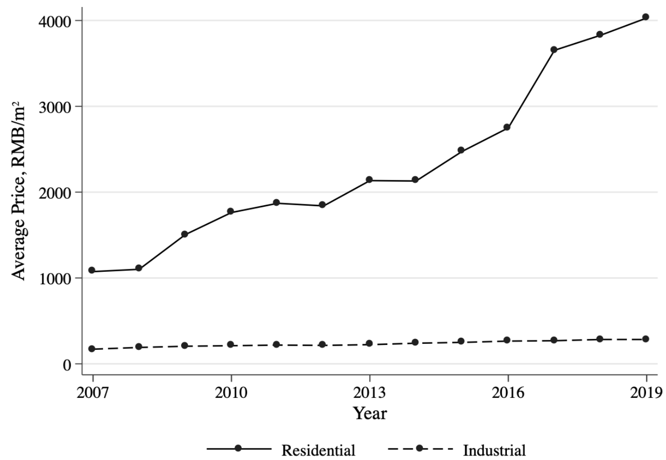



Figure 1: Average Land Prices over Time by Land Use: Industrial vs. Residential

Note: This figure reports the average price (per square meter) of residential and industrial land weighted by land size that are sold through auctions for each year during 2007–19.

their subsidiaries. We focus on land purchases during 2007–10 so that we can observe firms' postpurchase sales for at least three years in the ASIF dataset.

In total, we can merge 22,636 transactions out of a total 124,341 industrial land purchases by firms via agreement and auction during 2007–10. In the ASIF sample, around 3% of firm-year observations during 2003–13 were matched to land purchases during 2007–10. Table A.1 in the online appendix compares merged land parcels and firms to the universe of parcels and firms. Merged parcels are slightly more expensive and yet indistinguishable in terms of size and distance to the urban unit centers from the universe of land parcels. Land purchasing firms are also slightly larger than the universe of firms in terms of most metrics.

To estimate the incremental tax payments by home developers, we use data of listed home developers and city-level house prices and floor ratio during 2007–21.

**City data.** We collect city-level GDP and population data from the National Bureau of Statistics's Urban Statistic Yearbook during 2007–19.

## 3 Conceptual Framework

We begin with a general equilibrium model with residential and industrial land. The model demonstrates that the Pareto efficiency of land allocation can be conveniently characterized by a condition based on equilibrium variables. We then describe how to take this condition to the data and empirically evaluate it in the next section.

### 3.1 A Simple Model

We introduce industrial and residential land into the textbook general equilibrium model. The economy consists of an industrial and a residential sector, denoted by $\mathcal{I}$ and $\mathcal{R}$, respectively. Denote the output vector of firm $j$ by $y_j$ where elements with a positive (negative) value represent the firm's output (nonland input), and the land input by $L_{jI}$ or $L_{jR}$ depending on which sector the firm is in. The industrial firms are manufacturers that take industrial land as capital and produce goods forever after the land purchase, whereas residential firms are home developers that use residential land as intermediate inputs and then sell produced houses (to the consumer sector) only once. We regard goods at different times to be different goods; that is, each element in the vector $y_j$ represents an output/input good at a specific time.

Denote the price vector for nonland goods by $P$ and the price of industrial and residential land by $P_I$ and $P_R$, respectively. Prices are measured at time 0, with one of the nonland goods serving as the numeraire. The product $P \cdot y_j$ is the sum of the present value of firm j's pretax profits in all future periods except the initial land expense. To focus the analysis on land allocation efficiency, we assume all firms are price takers.

Denote the tax rate by $\tau$. Total present value of firm j's profits, $\pi_j$, can be written as

$$\pi_j = \begin{cases} P \cdot y_j(1-\tau) - P_I \cdot L_{jI}, & j \in \mathcal{I} \\ (P \cdot y_j - P_R \cdot L_{jR})(1-\tau), & j \in \mathcal{R}. \end{cases} \tag{1}$$

Equation (1) captures the differential tax treatment of the land cost across two uses: land is used as capital for industrial firms and intermediate input for residential firms.[5]

Consumers are indexed by $i$ and have locally nonsatiated preference. They have an endowment $\omega_i$ and receive a fraction $\theta_{ij}$ of firm j's profits. There is no tax on the consumers' side—importantly, there is no residential property tax, as in China. The government rebates all corporation taxes and land sale revenues to consumers as a lump sum, with $i$ receiving a fraction of $\theta_i$. This frictionless setting allows us to focus on the inefficiency arising from land allocation.

[5]For industrial firms, land acquisition costs are amortizable and tax-deductible for corporate income tax purposes. However, since value-added tax (VAT) is far more significant than income tax for these firms, we disregard the amortization of land acquisition costs for simplicity.

Consumers choose consumption $c_i$ and face the following budget constraint:

$$P \cdot c_i \leqslant P \cdot \omega_i + \sum_j \theta_{ij}\pi_j + \theta_i \Big( \sum_{j \in \mathcal{I}} (\tau P \cdot y_j + P_I \cdot L_{jI}) + \sum_{j \in \mathcal{R}} (\tau (P \cdot y_j - P_R \cdot L_{jR}) + P_R \cdot L_{jR}) \Big). \tag{2}$$

The goods and land markets clear if

$$\sum_i c_i = \sum_j y_j, \; \sum_j L_{jI} = L_I, \; \sum_j L_{jR} = L_R. \tag{3}$$

**Definition 1.** Given land allocation $(L_I, L_R)$, the competitive equilibrium is given by a price vector $(P^\star, P_I^\star, P_R^\star)$ and an allocation $\{y_j^\star, c_i^\star, L_{jI}^\star, L_{jR}^\star\}$ such that: i) firm j maximizes its profit; ii) consumer j maximizes utility; and iii) goods and land markets clear.

The following assumption ensures the competitive equilibrium is well behaved; it holds for production technology (say, Cobb-Douglas) commonly used in the literature.

**Assumption 1.** *The maximum output value of firm* $j$ *given its land input,* $Y_j(L_{js}; P) \equiv P \cdot y_j(L_{js}; P)$*, is twice differentiable, increasing, and weakly concave in its land input* $L_{js}$ *for* $s \in \{R, L\}$*.*

Throughout our analysis, we assume total available land is fixed at $\overline{L}$, i.e., $\overline{L} = L_I + L_R$. We are interested in the Pareto efficiency of the competitive equilibrium given land allocation $(L_I, L_R)$. Compared to the competitive equilibrium under $(L_I, L_R)$, would an alternative feasible land allocation benefit consumers? We have the following proposition.

**Proposition 1.** *Given* $(L_I, L_R)$*, the competitive equilibrium is Pareto efficient if and only if:*

$$\underbrace{\tau Y_k'(L_{kI}^\star; P^\star)}_{\textit{Industrial Tax}} + P_I^\star = \underbrace{\tau (Y_\ell'(L_{\ell R}^\star; P^\star) - P_R^\star)}_{\textit{Residential Tax}} + P_R^\star, \; \forall k \in \mathcal{I}, \ell \in \mathcal{R}. \tag{4}$$

Condition (4) says that the marginal payment for industrial land equals the marginal payment for residential land, both of which include the marginal increase in future tax payment and the upfront land price. Under competitive equilibrium, the LHS of (4) equals the marginal output of industrial land, $Y_k'(L_{kI}^\star; P^\star)$, and the RHS equals the marginal output of residential land, $Y_\ell'(L_{\ell R}^\star; P^\star)$. Therefore, (4) ensures equal marginal products of industrial and residential land.

One important assumption underlying Proposition 1 is that the demand side of the Chinese land market is competitive.[6] On the supply side that concerns local governments, it is worth

[6] Our data largely support this assumption. During the sample period of 2007–10, the average Herfindahl-Hirschman Index—a standard measure of market concentration based on the share of land purchased by different firms within a city—is roughly 4.2% for residential land and 3.5% for industrial land across cities.

emphasizing that the efficiency condition (4), which we use to assess land misallocation, does not rely on specific assumptions about the factors driving land allocation decisions. This is because condition (4) is evaluated using equilibrium prices and tax variables as inputs, treating the observed land allocation—regardless of its underlying determinants—as given.

As we will study in detail later, since industrial firms produce goods forever after the land purchase, they make permanent flows of tax payments, which implies that $\tau Y_k'(L_{kI}^\star; P^\star)$ in condition (4) could be quantitatively important. In contrast, in the context of China, residential land generates a one-time tax payment from home development only. Therefore, the key takeaway of Proposition 1 is that with industrial land paying more in the future and residential land paying more upfront, it is unclear whether or not Condition (4) holds in the data and if not, which type of land is oversupplied relative to the Pareto efficient level.[7]

### 3.2 Implied Discount Rate and Its Measurement

To empirically evaluate Condition (4), we need to calculate the price difference between residential and industrial land, $P_R^\star - P_I^\star$, the marginal increase in industrial tax payment, $\tau Y_k'(L_{kI}^\star; P^\star)$, and the marginal increase in residential tax payment, $\tau(Y_\ell'(L_{\ell R}^\star; P^\star) - P_R^\star)$. As explained above, unlike land prices paid by firms at the time of land purchase, industrial tax payments occur over time with industrial firms producing goods in all periods after the land purchase. Hence $\tau Y_k'(L_{kI}^\star; P^\star)$ represents the sum of a perpetual flow of tax payments. Residential firms build houses only once, and $\tau(Y_\ell'(L_{\ell R}^\star; P^\star) - P_R^\star)$ represents only temporary tax payments shortly after the land purchase.

To deal with the timing of the cash flow, one can calculate the present value of the future cash flows with estimates of the discount rates of industrial firms. Alternatively, we calculate the hypothetical discount rate such that Equation (4) holds and then compare this hypothetical discount rate with our preferred estimates of firms' discount rates. Specifically, we rewrite Equation (4) and define the implied discount rate (IDR) as follows:

$$\mathrm{IDR}_\tau \equiv \left\{ \rho : \underbrace{\sum_{t \geqslant \tau} \frac{Tax^I_{\tau,t}}{(1+\rho)^{t-\tau+1}}}_{\mathrm{PV(industrial\ tax)}} - \underbrace{\sum_{t \geqslant \tau} \frac{Tax^R_{\tau,t}}{(1+\rho)^{t-\tau+1}}}_{\mathrm{PV(residential\ tax)}} = \underbrace{P^R_\tau - P^I_\tau}_{\mathrm{IndDisc}} \right\}. \tag{5}$$

[7] In an economy with residential property tax, Proposition 1 shall be modified by introducing to the RHS of condition (4) the total present value of household property tax payments in the future. As the residential land price, $P_R^\star$, will be lower in the new equilibrium with property tax, the RHS of condition (4) should remain unchanged with the introduction of property tax.

Within the brace, $\mathrm{Tax}^{I}_{\tau,t}$ is industrial taxes per square meter of land in year $t$ due to industrial firms' land purchases in year $\tau$; $\mathrm{Tax}^{R}_{\tau,t}$ is residential taxes per square meter of land in year $t$ due to residential firms' land purchases in year $\tau$; and LHS is the difference in the present value of the future tax payments discounted by $\rho$ between industrial and residential land purchased at time $\tau$. The RHS is the extra upfront price that firms are willing to pay for a given land parcel if it is zoned as residential rather than industrial, which we shall refer to as "industrial discount" or $\mathrm{IndDisc}$ in this paper. We solve for $\rho$ such that the two are equal and define it as $\mathrm{IDR}_{\tau}$.

We can now assess the efficiency condition (4) by comparing $\mathrm{IDR}$ to firm's discount rates. If $\mathrm{IDR}$ is higher than firms' discount rates, then the marginal payment for one unit of industrial land, or the marginal output of industrial land, is higher than that of residential land, meaning that industrial land is undersupplied compared to the efficient level. If $\mathrm{IDR}$ is lower than firms' discount rates, then industrial land is oversupplied compared to the efficient level.

We clarify that $\mathrm{IDR}$ is *not* the pecuniary marginal return from the perspective of local governments who make zoning decisions. First, zoning land as residential versus industrial uses may involve different costs for local governments (e.g., displacement compensation to previous land occupants, required public services). Second, the marginal reallocation of land uses may lead to price impacts on other land parcels in the same administration sold by the same government; such price impacts are not reflected in the calculation of $\mathrm{IDR}$. In Section 5 we exploit supply-side factors that may shape the government land allocation decisions. Regardless of these supply-side factors, Proposition 1 gives a sufficient statistic for evaluating the misallocation of land resources.

# 4 Empirical Results

To calculate $\mathrm{IDR}$ by Equation (5), we first estimate the industrial discounts, the industrial tax payment and residential tax payment. We then combine these estimates to calculate $\mathrm{IDR}$s and evaluate land allocation efficiency.

## 4.1 Industrial Discount Estimation

The industrial discount as defined in Equation (5), $P^{R}_{t} - P^{I}_{t}$, measures the extra upfront price firms are willing to pay for a given land parcel if zoned for residential rather than industrial use. It differs from observed price differences between residential and industrial land parcels of differing quality. For example, parcels closer to city centers are more likely to be used as residential. We adjust for land quality to estimate the industrial discount in this section.

For each parcel $i$, let $P^R_{i,t}$ ($P^I_{i,t}$) denote the land's price per square meter if sold as residential (industrial). We use the sample of observed residential (industrial) sale prices to estimate a hedonic model predicting industrial (residential) parcels' prices if counterfactually sold as residential (industrial) (Wu et al., 2014; Chen et al., 2017). Formally, let $\mathcal{I}_R$ and $\mathcal{I}_I$ represent the sets of parcels observed to be residential and industrial, respectively. For $i \in \mathcal{I}_R$, we estimate the following regression specification:

$$P_{i,t} = X_{i,t} \cdot \beta^R + \gamma^R_{u,t} + \epsilon_{i,t}, \ \forall i \in \mathcal{I}_R. \tag{6}$$

To control for effects of local economic conditions (e.g., economic development, land market corruption), we construct granular "urban units," which are contiguous urban clusters identified by satellite images with average size of only 20 square kilometers. These urban units are close to towns and much more granular than cities or counties, the geographical unit typically controlled for in other studies.[8] We match land parcels to the closest urban unit and include urban unit–year fixed effects $\gamma^R_{u,t}$ to absorb unobservable local effects. To capture price variation across land parcels within urban units, we control for parcel characteristics $X_{i,t}$ including second-order polynomials of the log area of the land parcel, distance to the closest urban unit center, and the year-quarter the land is sold.

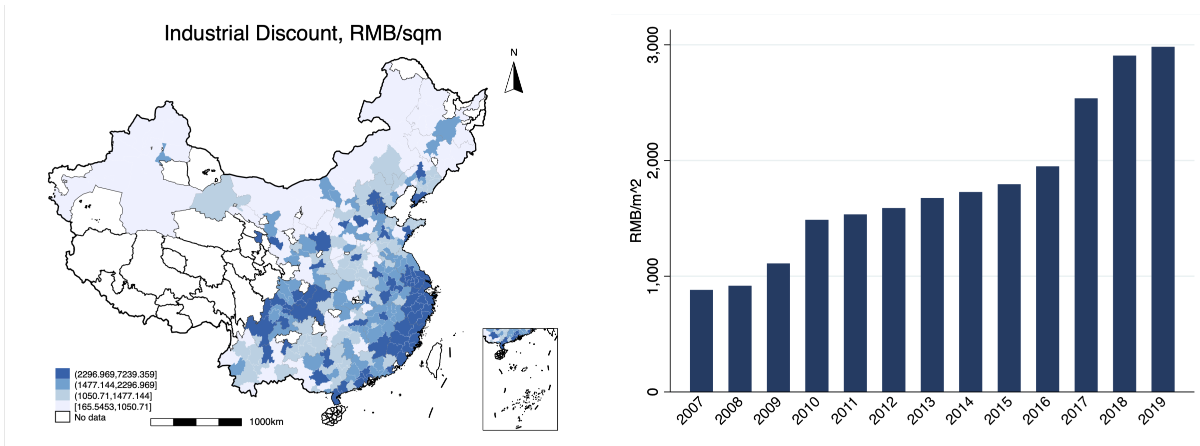
We estimate Eq. (6) by restricting the sample to the set of land parcels sold by auctions. To account for the possibility that the coefficients may vary over time and across cities, we estimate (6) separately for each prefecture city and separately for two time periods: 2007–10 and 2011–19. Since the specification (6) requires enough data to be estimated precisely, we restrict our estimation to cities and periods where we observe at least 80 (120) industrial land sales and 80 (120) residential land sales in the city during 2007–10 (2011–19). This leaves us with 213 (285) out of 341 cities for 2007–10 (2011–19), which collectively constitute 88.6% (98.4%) of all industrial and residential land sales through auction during 2007–10 (2011–19).

Using our estimates from the specification (6), we can then predict residential prices for industrial parcels by plugging these parcels' characteristics into Eq. (6):

$$\hat{P}^R_{i,t} = X_{i,t}\hat{\beta}^R + \hat{\gamma}^R_{u,t}, \ \forall i \in \mathcal{I}_I. \tag{7}$$

That is, $\hat{p}^R_{i,t}$ is the predicted price of parcel $i$ if sold as residential land. Analogously, we fit a hedonic model to industrial land parcels, with the same control variables as in (6):

[8] We describe details of this procedure in Online Appendix B.2.




(a) Industrial Discount Heatmap

(b) Industrial Discounts Over Time

Figure 2: Industrial Discount Estimates Summary.

Note: Panel (a) plots the average industrial land discount across all prefecture cities during 2007–19. Panel (b) shows the average industrial discount estimates across cities for each year from 2007 to 2019.

$$P_{i,t} = X_{i,t}\beta^I + \gamma^I_{u,t} + \epsilon_{i,t}, \ \forall i \in \mathcal{I}_I. \tag{8}$$

We then predict the counterfactual industrial prices for residential parcels as:

$$\hat{P}^I_{i,t} = X_{i,t}\hat{\beta}^I + \hat{\gamma}^I_{u,t}, \ \forall i \in \mathcal{I}_R. \tag{9}$$

Using our estimates of $\left\{P^R_{i,t}, P^I_{i,t}, \hat{P}^R_{i,t}, \hat{P}^I_{i,t}\right\}$, we calculate industrial land discount as:

$$\mathrm{IndDisc}_{i,t} = \begin{cases} P^R_{i,t} - \hat{P}^I_{i,t}, & i \in \mathcal{I}_R; \\ \hat{P}^R_{i,t} - P^I_{i,t}, & i \in \mathcal{I}_I. \end{cases}$$

We aggregate these land parcel level estimates, $\mathrm{IndDisc}_{i,t}$, to form city-year level estimates, $\mathrm{IndDisc}_{c,t}$, by taking averages of $\mathrm{IndDisc}_{i,t}$ weighted by each parcel's size. Figure 2 Panel (a) shows the heatmap of average industrial discounts during 2007–19 across different cities. Industrial discounts correlate strongly (0.52) with local economic development. Panel (b) plots the time series of the estimated industrial discounts. It was about 900 RMB/m$^2$ before 2009 and gradually increased over time. In 2019, it reached about 3,000 RMB/m$^2$, more than three times the 2007 level.

**Robustness checks.** We briefly comment on the assumptions required for our methodology to accurately measure industrial discounts. First, to predict counterfactual land prices under alternative zoning, there must be substantial overlap between the distributions of characteristics for industrial and residential land parcels. Appendix Figure A.2 illustrates that although residential land parcels tend to be larger and closer to city centers, the distributions have substantial overlap: our counterfactual price estimates are mostly interpolations rather than out-of-sample extrapolations.

Second, to assess land allocation efficiency, the *marginal* land parcels whose use is more likely to change following a marginal reallocation of land supply should be more relevant. In Appendix Section B.4, we demonstrate an approach that can identify marginal land parcels fairly well and put more weight on these marginal parcels in calculating the industrial land discount. We find that the industrial discount estimates based on marginal land parcels are quite similar to those in our baseline specification, with the absolute difference being about 4% of the baseline estimates.

Third, differences between industrial and residential parcels that are not captured by our controls could bias counterfactual price estimates. Such unobservable characteristics most likely cause upward bias to the industrial land discount estimates: for example, if certain unobserved characteristics cause residential land to be used as residential, then without controlling for these characteristics the counterfactual residential price estimates for industrial land would be inflated. This only *strengthens* our takeaway that future industrial tax payments are quantitatively important relative to the industrial discount.

Fourth, the size of bias from unobserved factors is likely not quantitatively large. Although land parcels' features used in our pricing models—Eqs. (6) and (8)—explain 50% of land prices' variation, controlling for observable characteristics only changes average industrial discounts by around 10%, so selection on observable characteristics has little effect on estimated industrial discounts. For unobservable characteristics to sizably affect our results, they must both be key land price drivers and differ greatly for industrial and residential parcels, as Oster (2019) argues.

Corruption is an unobserved factor known to drive land prices (Chen and Kung, 2019; Li, 2019). Our method does not require the absence of corruption but assumes no difference in corruption between observed and counterfactual residential and industrial land sales. For instance, if half of observed residential land sales are corrupt and corruption lowers prices by 20%, our estimates are valid if industrial parcels face similar corruption and price-reduction levels if used as residential. There is no particular reason to believe corruption would differ on industrial land parcels if zoned as residential, since corruption is a city-level rather than parcel-level phenomenon.

### 4.2 Industrial Tax Estimation

To estimate the marginal effect of industrial land purchases on tax payments, we first employ a differences-in-differences (DID) regression to estimate the effect on firms' sales revenue, and then multiply the revenue increase by the effective industrial tax rate.

#### 4.2.1 The Effect of Land Purchase on Sales

For a given event year $\tau_j$, some firm j purchases a land parcel of size $\Delta_j$. We assume firm j's sales in period t, $S_{j,t}$, take the following form:

$$\frac{S_{j,t}}{S_{j,\tau_j-1}} = \begin{cases} \alpha_j + \eta_{p(j),I(j),t,\tau_j} + \varepsilon_{j,t} & t < \tau_j, \\ \alpha_j + \eta_{p(j),I(j),t,\tau_j} + \theta_{t-\tau_j+1} \cdot \frac{\Delta_j}{S_{j,\tau_j-1}} + \varepsilon_{j,t} & t \geqslant \tau_j. \end{cases} \tag{10}$$

Eq. (10) states that changes in firms' sales are determined by time-varying province-by-industry shock $\eta_{p(j),I(j),t,\tau_j}$, time-invariant firm-specific factors $\alpha_j$, and land purchases $\Delta_j$. The parameter $\theta_{t-\tau_j+1}$ captures the dollar increase in firm sales per unit of land purchase.

In the data, we consider treated firms to have $\Delta_j > 0$ and control firms $\Delta_j = 0$. For cleaner identification, we restrict treated firms to those that purchased land during only one year in our sample period, and control firms to those that acquired no industrial land over the sample period.

The challenge with estimating $\theta_{t-\tau_j+1}$ in Eq. (10) is that land purchase decisions may be correlated with shocks $\varepsilon_{j,t}$ for $t \geqslant \tau_j$, i.e., $E[\varepsilon_{j,t} \cdot \frac{\Delta_j}{S_{j,\tau_j-1}} | \alpha_j, \eta_{p(j),I(j),t,\tau_j}, \tau] \neq 0$. These shocks can be decomposed as

$$\varepsilon_{j,t} = f_t(p(x_{j,\tau_j-1})) + e_{j,t}, \; t \geqslant \tau_j. \tag{11}$$

In this decomposition, $f_t$ can be of any function form, and $p(x_{j,\tau_j-1})$ is a firm's probability of purchasing land given observables $x_{j,\tau_j-1}$. We assume that the correlation between land purchase decisions and shocks $\varepsilon_{j,t}$ can be fully summarized by $f_t(p(x_{j,\tau_j-1}))$. Formally, we make the following identifying assumption:

$$\mathbb{E}[e_{j,t} \mathbf{1}_{\Delta_j>0} \mid \alpha_j, \eta_{p(j),I(j),t,\tau_j}, \tau] = 0, \; \forall \tau. \tag{12}$$

In words, $e_{j,t}$ is uncorrelated with the land purchase decision. We view this as a plausible identifying assumption and, moreover, one we can partially test by examining pretrends in sales among treatment and control firms.

Motivated by this framework, we match treated firms with control firms based on land purchase propensity scores using firm characteristics in year $t = \tau_j - 1$. After stratifying by event year, province, and two-digit National Industries Classification code, we estimate $\hat{p}(x_{j,\tau_j-1})$ based on the three following observables at the firm level:

$$x_{j,\tau_j-1} = \left\{ \log(S_{j,\tau_j-1}), \log(S_{j,\tau_j-2}), \frac{\mathtt{Profit}_{j,\tau_j-1}}{S_{j,\tau_j-1}} \right\}.$$

Here, $S_{j,t}$ is firm j's sales in year t and $\mathtt{Profit}_{j,t}/S_{j,t}$ is firm j's profit margin in year t. We find these three variables are predictive of land purchase decisions. Following the literature (Dehejia and Wahba, 1999; Blundell and Costa Dias, 2000; Smith and Todd, 2005), we match firms based on two years of pretreatment sales data to deliver robust and consistent estimates of the treatment effect. Equally important, after matching, one test of our assumption about the residuals $\varepsilon_{j,t}$ will be whether treated and control firms exhibit parallel trends in sales before $\tau_j$. In our event study analysis below, we test this and fail to reject parallel trends for all purchase cohorts $\tau$.

We estimate the effects of land purchase, $\theta_{t-\tau_j+1}$, using DID on the matched sample. To do so, we define the average treatment among treated as

$$\overline{\frac{\Delta}{S}}_{(\tau,p,I)} \equiv \mathbb{E}\left[ \frac{\Delta_j}{S_{j,\tau_j-1}} \mid \Delta_j > 0, \tau_j = \tau, p(j) = p, I(j) = I \right]. \tag{13}$$

Using Eq. (10), firm sales can be written as

$$\frac{S_{j,t}}{S_{j,\tau_j-1}} = \alpha_j + \eta_{p(j),I(j),t,\tau_j} + \theta_{t-\tau_j+1} \cdot \mathbf{1}_{\Delta_j>0} \cdot \overline{\frac{\Delta}{S}}_{(\tau,p,I)} + \varepsilon'_{j,t}, \tag{14}$$

where we define

$$\varepsilon'_{j,t} \equiv \begin{cases} \varepsilon_{j,t}, & \Delta_j = 0; \\ \varepsilon_{j,t} + \theta_{t-\tau_j+1} \cdot (\frac{\Delta_j}{S_{j,\tau_j-1}} - \overline{\frac{\Delta}{S}}_{(\tau,p,I)}), & \Delta_j > 0. \end{cases} \tag{15}$$

Note that,

$$\mathbb{E}[\varepsilon'_{j,t} \cdot \mathbf{1}_{\Delta_j>0} \overline{\frac{\Delta}{S}}_{(\tau,p,I)} \mid \alpha_j, \eta_{p(j),I(j),t}] = 0, \tag{16}$$

The equation follows from (12) given the definition of $\overline{\frac{\Delta}{S}}_{(\tau,p,I)}$. Per Eq. (16), we can consistently estimate $\theta_{t-\tau_i+1}$ with DID estimation using specification (14).

Figure 3 reports the estimates of specification (14) by pooling all 2007–10 purchase years.[9] We start from 2007, the first year of the land sale data; we end in 2010, the last land purchase year for which we have at least three years of postpurchase firm tax data (i.e., 2011–13) to estimate the permanent impact on taxes. For each purchase year $\tau \in \{2007, 2008, 2009, 2010\}$, we take $t = \tau - 1$ as the base year and use data from years $\tau - 4$ (few firms have data before $\tau - 4$) through 2013.

Figure 3 reveals three important patterns. First, the estimated treatment effects are positive and

[9] Table A.4 in the Online Appendix reports estimates for each purchase year.

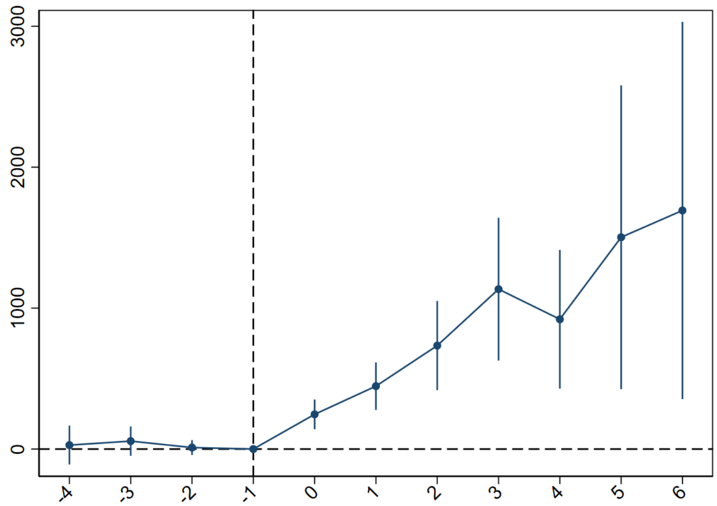



Figure 3: Dynamic Treatment Effect of Land Purchase on Sales

Note: This figure plots the 95% confidence interval for the event study coefficient estimates using Equation (14).

significant (economically and statistically). Second, estimated treatment effects grow over time. Third, and importantly for validating our matched DID identification assumptions, treated and control firms are not significantly distinguishable prior to land purchase. Note that our matching procedure guarantees that the parallel trend holds from $t = \tau - 2$ to $t = \tau - 1$, but not before. The fact that the parallel trend additionally holds from $t = \tau - 4$ to $t = \tau - 2$ lends some support to our identification assumption.

Motivated by these patterns, Table 2 summarizes the estimated treatment effects more concisely: we separately estimate a treatment effect for the first three years after purchase that captures more modest effects as firms presumably made other fixed investments (e.g., new plants) complementing the land purchase and another treatment effect for the third and subsequent years capturing new land's long-run effects. To circumvent potential issues due to staggered treatment in the pooled regression (De Chaisemartin and d'Haultfoeuille, 2020; Baker et al., 2022), we use the stacked DID by allowing for treatment-specific time-fixed effect (Cengiz et al., 2019; Deshpande and Li, 2019).

Formally, we estimate

$$\frac{S_{j,t}}{S_{j,\tau_j-1}} = \alpha_j + \eta_{p(j),I(j),t,\tau_j} + \theta_{\text{short}} \cdot \mathbf{1}_{\Delta_j>0,t-\tau_j\in\{0,1,2\}} \cdot \overline{\frac{\Delta}{S}}_{(\tau,p,I)} + \theta_{\text{long}} \cdot \mathbf{1}_{\Delta_j>0,t-\tau_j>2} \cdot \overline{\frac{\Delta}{S}}_{(\tau,p,I)} + \varepsilon'_{j,t} \quad (17)$$

In Eq. (17), the subscript $\tau$ is the event year for the treated and the matched control firms. It is stacked DID, as the time fixed effect varies with $\tau_j$.

Table 2: Baseline Estimation of Marginal Output of Land

| Event Year | 2007–2010 | | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| Dep Var: Sale | (1) | (2) | (3) | (4) | (5) | (6) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t-\tau\in\{0,1,2\}}$ | 399.5*** | 363.9*** | 236.4*** | 285.0** | 277.6*** | 773.7*** |
| | (6.195) | (4.816) | (2.850) | (2.457) | (3.956) | (4.109) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t-\tau\geqslant 3}$ | 1,027*** | 1,096*** | 1,114** | 2,112*** | 551.7** | 1,253*** |
| | (5.185) | (4.489) | (2.291) | (3.145) | (2.221) | (3.324) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t-\tau\in\{0,1,2\}} \cdot \mathrm{H2}$ | | 77.78 | | | | |
| | | (0.611) | | | | |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t-\tau\geqslant 3} \cdot \mathrm{H2}$ | | -144.3 | | | | |
| | | (-0.385) | | | | |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-Industry-Year FE | | | Yes | Yes | Yes | Yes |
| Event Year-Province-Industry-Year FE | Yes | Yes | | | | |
| Observations | 43,008 | 43,008 | 9,236 | 4,088 | 13,003 | 16,681 |
| R-squared | 0.662 | 0.662 | 0.673 | 0.673 | 0.656 | 0.660 |

Note: This table reports estimation results of Model (17) with the matched sample. We drop the matched pairs whenever the treated or the control firm exits the sample. The first estimate is for $\theta_{\text{short-run}}$ and the second is for $\theta_{\text{long-run}}$. For each treatment year $\tau \in \{2007, 2008, \ldots, 2010\}$, the sample ranges from $\tau - 4$ to 2013 (but the data for 2010 are missing). The variable "sales" is in 1,000 RMB and $\bar{\Delta}$ is in 1,000m$^2$. Standard errors are clustered by firms. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Table 2, we report these estimates using land sales in 2007–10 in Columns (1)-(2), and the estimated effects for each event year in the next four columns. On average, land purchases generate an additional 399.5 RMB/m$^2$ in sales per year in the first three years, and a long-run effect of 1027 RMB/m$^2$ in sales per year in subsequent years.[10]

Despite parallel pretrends between treated and control firms, the identification assumption (12) could still be violated if treated firms acquire new land in response to a contemporaneous positive shock. We contend this is unlikely. When impacted by an unexpected positive shock, firms will first choose on-site plant expansion to increase production capacity. Only when experiencing significant diseconomies associated with on-site expansion will they consider establishing new plants, which necessitates thorough market research and site selection (Schmenner, 2005). Thus, it seems improbable that firms could acquire new land in the same year as they are hit by a positive shock.

We conduct a test to support our argument. If firms' land purchases could respond to shocks in the same year, land purchases in the second half of the year is more likely to be a result from

[10] As the data for 2010 are missing, we lack one year of observations for either the first three years or the later years, depending on the land purchase year $\tau$.

the shock than purchases in the first half of the year. Thus, the potential positive bias should be greater for firms that purchase land in the second half of the year. But Table 2 Column (2) does not support this prediction: when we interact the treatment effect with a dummy H2 that equals one for firms purchasing land in the second half of the year and zero otherwise, the estimated treatment effect is similar, whichever half of the year firms purchased the land.

Lastly, we discuss one econometric issue regarding panel imbalance, which can arise due to censoring when firm sales fall below thresholds for inclusion in our data. We address imbalance by excluding matched treated-control pairs from our estimation whenever either firm's data are imbalanced. In Online Appendix B.5, we study the causes of panel imbalance and conclude it is largely due to idiosyncratic data linkage issues, such as name changes or reporting inconsistencies. We also find a modest amount is due to censoring, which makes our estimates of land-purchase treatment effects conservative.

#### 4.2.2 Firm Tax Estimation

We now calculate the marginal tax payment following firms' land purchases. In the model in Section 3.1, additional land supply to firm j only impacts j's production and tax payment. In the data, firms may have idle capacity and could also benefit from downstream firms' land purchases. We can think of the supplier firms' production as a function of both their own and downstream firms' land input. Therefore, the marginal willingness to pay for an industrial land parcel by firms, which is the marginal output of an industrial land parcel in any competitive equilibrium, equals total tax payment from both the land-purchasing and the supplier firms, in addition to the upfront land price.

The most important taxes industrial firms pay are value-added taxes (VAT) and corporate income taxes. Both are approximately linear in the firm's value added.[11] Because the total value added of the land-purchasing firm and its suppliers equals the sales of the land-purchasing firm, the total increase in value added is the sale increase of the land-purchasing firm estimated above. What remains is to estimate effective tax rates.

We estimate these rates by regressing total VAT payment from the land-purchasing and its supplier firms on these firms' total value added, which is the sales of the purchasing firm, using the annual sample of industrial firms. Averaging across firms, we see a pretty linear relationship:

[11] For a detailed description of the system of firm taxation in China, see Online Appendix B.7.

the average value-added tax rate (approximately 12.10%) is stable across firms of different sizes. Combining income taxes and other administrative fees, which amount to approximately 5.77% of firms' value added, we reach an average tax rate of 17.87%. The Online Appendix B.7 provides more details on the calculation.

Multiplying the 17.87% tax rate by the DID estimate of the effect of land purchases on sales revenue from column (1) of Table 2, we obtain the marginal effects of land purchases on tax payment: 71.4 RMB/$m^2$ for the first three years after land acquisition and 183.5 RMB/$m^2$ afterwards.

Finally, to map these tax estimates to $Tax^I_{\tau,t}$ in Equation (5), we assume that the tax payment per square meter of land in year $t$ is proportional to $Z_t$, the economy-wide productivity that drives tax growth, and $Tax^I_{\tau,t}$ is given by:

$$Tax^I_{\tau,t} \equiv \begin{cases} Tax^I_{short} \times Z_t, & t-\tau \in \{0,1,2\}; \\ Tax^I_{long} \times Z_t, & t-\tau > 2. \end{cases} \tag{18}$$

Equation 18 captures firms' dynamics after acquiring land: firms are still engaged in business development for the first three years and achieve full capacity after the third year. Recall that our two industrial tax estimates are based on 2007-10 land acquisitions and firm sales data until 2013 (missing 2010 data). The relationship between these two estimates and Equation (18) is:

$$71.4 = Tax^I_{\text{short}} \times \sum_{\tau \geqslant 2007}^{2010} n_\tau \cdot \frac{\sum_{\tau \leqslant t \leqslant \tau+2, t \neq 2010} Z_t}{\sum_{\tau \leqslant t \leqslant \tau+2, t \neq 2010} 1},$$
$$183.5 = Tax^I_{\text{long}} \times \sum_{\tau \geqslant 2007}^{2010} n_\tau \cdot \frac{\sum_{\tau+2 < t \leqslant 2013, t \neq 2010} Z_t}{\sum_{\tau+2 < t \leqslant 2013, t \neq 2010} 1},$$

where $n_\tau$ is the share of observations for event year $\tau$ in the estimation of Table 2 Column (1). We proxy $\{Z_t\}$ with aggregate tax revenues during 2007–24. Aggregate tax revenue growth slowed down in this period, from 18.8% in 2008 to 3.2% over 2021–24. To be conservative, we assume a long-run growth rate of zero after 2024.[12] We scale the time series of $\{Z_t\}$ such that $Tax^I_{\text{short}} = 71.4$, and $Tax^I_{\text{long}}$ is calculated accordingly.

[12]Assuming a high permanent growth rate after 2024, say 2%, only increases our IDR estimate during 2007–10 by approximately 0.5%.

#### 4.2.3 City-level Estimates

Conducting the estimation for each city to obtain city-level industrial tax estimates is challenging because of limited observations in many cities. We note that IDR is roughly the ratio between industrial tax and the industrial land discount plus the residential tax. Thus, the IDR estimate would be unbiased if the estimation error of the industrial tax is uncorrelated with the industrial discount plus residential tax. To this end, we let the marginal effect of land purchase on firm sales, $\theta$, vary with the city-level industrial discount plus residential tax at the time of land purchase.

Formally, define:

$$X_{c,\tau} = IndDisc_{c,\tau} + ResTax_{c,\tau}, \tag{19}$$

where $ResTax_{c,\tau}$ is the amount of residential tax per square meter of land in city $c$ year $\tau$, which will be estimated in the following section.

We modify specification (10) as follows:

$$\begin{aligned}\frac{S_{j,t}}{S_{j,\tau_j-1}} =& \alpha_j + \eta_{p(j),I(j),t,\tau_j} + (\theta^0_{short} + \theta^1_{short} \cdot X_{c(j),\tau_j}) \cdot \mathbf{1}_{t-\tau_j \in \{0,1,2\}} \cdot \frac{\Delta_j}{S_{j,\tau_j-1}} \\ &+ (\theta^0_{long} + \theta^1_{long} \cdot X_{c(j),\tau_j}) \cdot \mathbf{1}_{t-\tau_j > 2} \cdot \frac{\Delta_j}{S_{j,\tau_j-1}} + \varepsilon_{j,t}.\end{aligned} \tag{20}$$

Define:

$$\overline{\frac{X \cdot \Delta}{S}}_{(\tau,p,I)} \equiv \mathbb{E}\left[\frac{X_{c(j),\tau_j} \cdot \Delta_j}{S_{j,\tau_j-1}} \mid \Delta_j > 0, \tau_j = \tau, p(j) = p, I(j) = I\right]. \tag{21}$$

Equation (20) can then be written as:

$$\begin{aligned}\frac{S_{j,t}}{S_{j,\tau_j-1}} =& \alpha_j + \eta_{p(j),I(j),t,\tau_j} + \theta^0_{short} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j \in \{0,1,2\}} \cdot \overline{\frac{\Delta}{S}}_{(\tau,p,I)} + \theta^0_{long} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j>2} \cdot \overline{\frac{\Delta}{S}}_{(\tau,p,I)} \\ &+ \theta^1_{short} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j \in \{0,1,2\}} \cdot \overline{\frac{X \cdot \Delta}{S}}_{(\tau,p,I)} + \theta^1_{long} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j>2} \cdot \overline{\frac{X \cdot \Delta}{S}}_{(\tau,p,I)} + \varepsilon'_{j,t},\end{aligned} \tag{22}$$

where $\varepsilon'$ is defined accordingly as in Equation (15). Similarly, we have

$$\mathbb{E}[\varepsilon'_{j,t} \cdot \mathbf{1}_{\Delta_j>0} \overline{\frac{\Delta}{S}}_{(\tau,p,I)} \mid \alpha_j, \eta_{p(j),I(j),t}] = 0,$$
$$\mathbb{E}[\varepsilon'_{j,t} \cdot \mathbf{1}_{\Delta_j>0} \overline{\frac{X \cdot \Delta}{S}}_{(\tau,p,I)} \mid \alpha_j, \eta_{p(j),I(j),t}] = 0.$$

Therefore, we can consistently estimate $\theta$ with DID using specification (22). The estimation reveals that:

$$(\theta^0_{short}, \theta^0_{long}, \theta^1_{short}, \theta^1_{long}) = (54.0,\ 535.3,\ 0.09,\ 0.13).$$

The positive estimates of $\theta^1$ imply land purchase's marginal effect on firm sales is higher in cities with higher industrial discount where local productivity tends to be higher. Multiplying the sale increase by the average tax rate, the city-level estimates of the average increase in industrial tax are then $(9.7 + 0.016 \cdot X_c)$ RMB/m$^2$ in the first three years after land acquisition and $(95.6 + 0.023 \cdot X_c)$ RMB/m$^2$ afterwards, where $X_c$ is the average value of $X_{c,\tau}$ over 2007–10.

We map these estimates to the city-level $Tax^I_{c,\tau,t}$ using the same procedure as above:

$$Tax^I_{c,\tau,t} \equiv \begin{cases} Tax^I_{c,short} \times Z_t, & t - \tau \leqslant 2; \\ Tax^I_{c,long} \times Z_t, & t - \tau > 2, \end{cases} \tag{23}$$

where $Tax^I_{c,\text{short}} = 9.7 + 0.016 \cdot X_c$ and $Tax^I_{c,\text{long}} = (95.6 + 0.023 \cdot X_c) \cdot \frac{Tax^I_{\text{long}}}{183.5}$.

#### 4.2.4 Complementary Evidence

Our estimates of tax payment from industrial land sales square fairly well with the following two pieces of complementary evidence.

**Average VAT income from industrial land.** As a first benchmark, we compare our estimated marginal increase in tax payments on industrial land to the average VAT per square meter of land, which we calculate using total VAT payment reported in China Tax Yearbook divided by total industrial land size reported in China City Construction Yearbook.[13] Appendix Figure A.6a shows the average VAT payment per square meter of land for each province in 2011, right after the 2007–10 sample period used to estimate the marginal tax payment. Across all provinces, the average VAT payment per square meter of land is 332 RMB/m$^2$. This has the same magnitude as, though is slightly larger than, our estimates of long-run increase in marginal tax payment, 183.5 RMB/m$^2$.

**Official guidance on minimum required tax on industrial land.** For a second source of data on tax payment, we use the government's direct guidance on the "required minimum" tax payment on industrial land. In 2008, the Ministry of Land Resources issued its Guidelines on Land Supply to Industrial Projects, which required local land bureaus to impose restrictions on the industrial land supply.[14] Some provincial land bureaus added additional requirements on firms' tax payments, with Jiangsu province being the first to explicitly impose an industry-specific

[13]We calculate the total VAT paid by firms in each province as the summation of both the local governments' and the central government's VAT revenues.

[14]These restrictions include the amount of fixed investment, floor ratio, the fraction of land for buildings and construction, and the fraction of land for offices and utilities.

minimum requirement on firms' industrial land tax payments in 2018. Some provinces, such as Hunan, followed and imposed the same minimum requirement in 2020.

Appendix Figure A.6b plots the industry-specific minimum requirement on annual tax payments set by Jiangsu and Hunan provinces for manufacturing industries. The minimum tax requirement for most industries is around 100 RMB/m$^2$. The average minimum tax requirement across industries weighted by the industrial composition of land sales during 2007–10 is about 71.4 RMB/m$^2$. Our marginal tax estimate of 183.5 RMB/m$^2$ accords with these minimum requirements.

### 4.3 Residential Tax Estimation

As in the estimation of industrial taxes, residential development will generate tax payment not only from home developers that acquire land, but also from upstream suppliers, both of which shall be included in the calculation of residential tax. We estimate a distinct tax rate paid by home developers because the tax structure of home developers differs from manufacturers' in terms of tax items and rates. For taxes paid by upstream suppliers, since they are also manufacturers, we will apply the same methodology as in the calculation of industrial taxes. After a home is sold, there will be no further taxes as there are as of yet no residential property taxes in China.

Unlike industrial taxes that occur every year after land purchases, residential taxes are temporary; we need to take a stance on their timing. In practice, some developer taxes (e.g., deed taxes, the stamp tax) are paid during land acquisition; other developer taxes (e.g., value-added and income taxes) are paid when the houses are "advance sold," which generally occurs within three years of land acquisition. Upstream taxes are paid during the construction process. For simplicity, we assume all residential taxes occur in the year following land acquisition:

$$\mathsf{Tax}^{R}_{c,\tau,t} = \mathbf{1}_{t=\tau+1} \times \mathsf{ResTax}_{c,t},$$

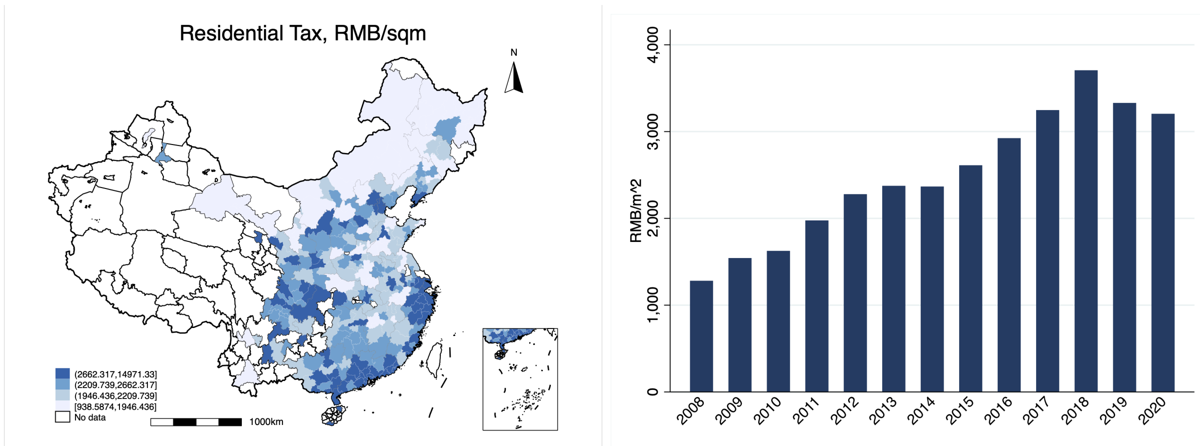
where $\mathsf{ResTax}_{c,t}$ denotes tax payment per square meter of land in city $c$ and year $t$.[15]

We calculate $\mathsf{ResTax}_{c,t}$ as:

$$\mathsf{ResTax}_{c,t} = (P^{h}_{c,t} \times \mathsf{DevTaxRate}_{t} + \mathsf{Cost}_{c,t} \times \mathsf{IndTaxRate}) \times \mathsf{FloorRatio}_{c}, \tag{24}$$

where $P^{h}_{c,t}$ is the average house price per square meter of livable space, $\mathsf{DevTaxRate}_{t}$ is the tax rate that developers pay proportional to home sales, $\mathsf{Cost}_{c,t}$ is the average construction cost per

[15]In Section 4.4.2 we consider the alternative case in which $\mathsf{ResTax}$ occurs two years later and show that our results are robust to this choice.




(a) Residential Tax Heatmap

(b) Residential Tax over Time

Figure 4: Residential Tax Estimates Summary.

Note: Panel (a) plots the average residential tax across prefecture cities during 2007–19. Panel (b) shows the average residential tax estimates across cities for each year from 2007 to 2019.

square meter of livable space including the cost of all intermediate inputs, $\mathtt{IndTaxRate}$ is the estimated industrial tax rate from Section 4.2.2, and $\mathtt{FloorRatio}_c$ is the average amount of livable space built per square meter of land.

We calculate $P^h_{c,t}$ using total house sale revenues over the total livable area of houses sold in city $c$ and year $t$. To get $\mathtt{DevTaxRate}_t$, we use data on listed developers in year $t$ and regress the firms' total annual taxes on annual sales.[16] Figure A.7 in the Online Appendix shows the relationship between the developers' annual taxes and their sales is close to linear for any year, suggesting that $\mathtt{DevTaxRate}_t$ is independent of developer size. The intermediate cost $\mathtt{Cost}_{c,t}$ is the average value reported by local developers to China's National Bureau of Statistics. We measure $\mathtt{FloorRatio}_c$ using the average value across all residential land parcels sold in city $c$ during 2007–19 weighted by parcel size; city-level floor ratio varies little over time.

Figure 4 Panel (a) plots the average residential tax during 2007–19 across prefecture cities. Residential tax correlates strongly with local GDP per capita, with a correlation of 0.63. Panel (b) shows that the average amount of residential taxes is increasing over time.

[16] Since May 1, 2016, home developers have paid value-added taxes, which are not reported in their income statements. We estimate the value-added taxes using (Sales-COGS)$\times$ VAT tax rate and then add them to the reported taxes.

Table 3: Industrial Discount, Tax and IDR

| | IndDisc | Industrial Tax | | Residential Tax | IDR |
|---|---|---|---|---|---|
| Baseline | 1794.2 | 71.4 | 183.5 | 2029.0 | 6.3% |
| Exclude Five-Yr-Plan-targeted industries | 1742.3 | 65.2 | 133.8 | 1964.4 | 5.0% |
| Full Tax Deduction | 1794.2 | 53.5 | 183.5 | 2029.0 | 6.3% |
| Two-year gap of Developer Taxes | 1794.2 | 71.4 | 183.5 | 2349.5 | 5.9% |
| Combination of three adjustments | 1742.3 | 48.9 | 133.8 | 2290.8 | 4.6% |

Note: This table shows the industrial discount estimates during 2007–10, the tax benefits, and the corresponding IDR. We aggregate the city-year level industrial discounts and residential tax payments to the national level, all weighted by the purchased land size of the treated firms in the estimation of industrial tax payment in Column (1) Table 2. We conduct robustness checks by excluding Five-Year Plan targeted industries (the second row), deducting the maximum tax rebates of 25% in the first five years (the third row), assuming the residential tax cash flow occurring two years after land acquisition (the forth row), and the combination of the three adjustments (the last row). In Row 2 and 5, we set the weight to be purchased land size of treated firms in nontargeted industries to match the industrial tax estimation.

## 4.4 IDR and Land Allocation Efficiency

In this section, we combine the estimates of industrial discount and tax payments to calculate IDR. We focus on 2007–10, the sample period for which we estimate the industrial tax payments. We first calculate IDR at the national level to assess the overall over- or undersupply of industrial relative to residential land. We then calculate IDR for each city to evaluate the geographic distribution of land allocation efficiency. Finally, we calculate the IDR over time to shed light on land allocation efficiency in recent years.

### 4.4.1 National IDR during 2007–10

In 2007–10, the industrial land discount $\mathsf{IndDisc}_{c,\tau}$ and residential tax $\mathsf{Tax}^{R}_{c,\tau,\tau+1}$, weighted by treated firms' land purchase size in city $c$ and year $\tau$ used in Column (1) of Table 2, are on average 1794.2 RMB/m$^2$ and 2029 RMB/m$^2$, respectively. We calculate national IDR during 2007–10 as the discount rate $\rho$ that equates the average value of the LHS and RHS within the brace in Equation (5), weighted by the size of treat firms' land purchases in city $c$ and year $\tau$. Such IDR = 6.3%.

What would be the appropriate firm discount rate to compare with IDR? Our preferred choice is firms' cost of capital $R_A$, a corporate finance concept that is used to discount firms' free cash flow to obtain their present value (Berk and DeMarzo, 2017). We prefer $R_A$ because firms' tax payment and free cash flow share similar risk profiles, which makes $R_A$ an appropriately risk-adjusted discount rate for the firms' future tax payment.[17] Using publicly listed industrial firms, we estimate the average $R_A$ to be 8.0% during 2007–10.

Comparing our baseline estimate of IDR with $R_A$ of 8.0%, we find that firms' marginal willingness to pay for one unit of industrial land, or the marginal output of industrial land, is smaller than that of residential land, suggesting a relative oversupply of industrial land. However, contrary to the conventional view that industrial land is heavily subsidized relative to residential land, countrywide industrial land is only slightly oversupplied relative to the residential land. The long-run tax payment from the industrial land is quantitatively important as part of the payment from firms for industrial land.

#### 4.4.2 Robustness Checks

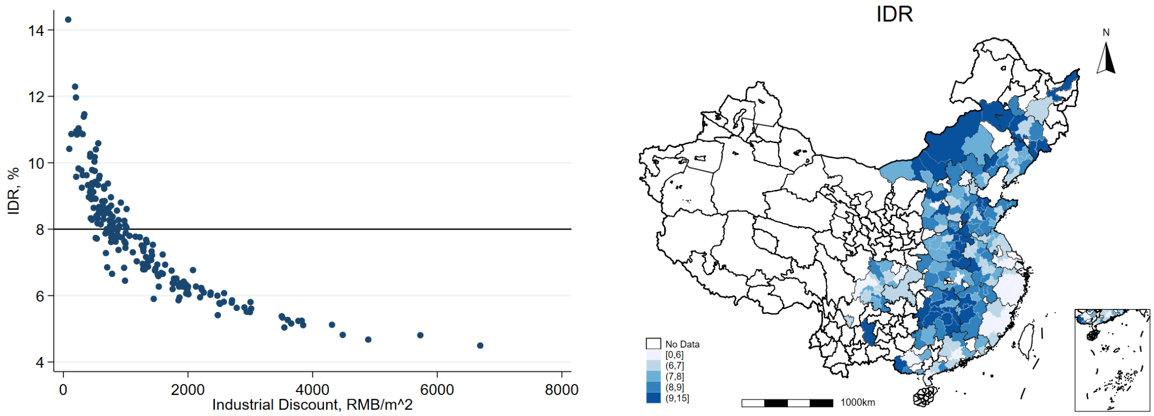
We conduct several robustness checks to examine whether we may have significantly overestimated the importance of future tax payment in calculating IDR. First, we calculate IDR separately for industries based on whether they were ever targeted in China's Five-Year Plans, which highlight key sectors the government planned to support during 2006–15 (Cen et al., 2021). Firms in targeted industries may have received additional government subsidies, which should have been deducted from their total payment for industrial land when calculating IDR.[18] We estimate IDR for targeted industries to be 7.2%, which is indeed modestly higher than IDR of 5.0% for nontargeted industries. However, accounting for industrial policy–targeted industries does not substantially affect our IDR estimates as 5.0% is only slightly smaller than the baseline estimate.

Second, local governments sometimes offer tax rebates for new firm entrants in their first operating years, which shall also be deducted from firms' industrial land payments. The third row of Table 3 shows how our IDR estimate changes assuming the most conservative case where firms receive 25% tax rebates in their first five years: IDR is reduced by less than 0.1% from the baseline level.

Third, we consider alternative timing of residential tax cash flows by assuming these cash flows all occur two years after land purchase. Estimated residential tax rises to 2349.5 RMB/$m^2$, and IDR decreases marginally to 5.9% as shown in the fourth row.

[17] We do not use the weighted average cost of capital (WACC) because there is no tax shield associated with the industrial tax payment. Appendix Section B.11 provides details on the estimation of $R_A$.

[18] Table A.5 in the online appendix shows the list of targeted industries. In our sample, among all the treated firms, 57.0% (43.0%) are from targeted (nontargeted) industries and they account for 62.7% (37.3%) of the size of the matched industrial lands.




(a) IDR versus IndDisc

(b) IDR City Heatmap

Figure 5: Geographic Distribution of Land Allocation Efficiency

Note: Panel (a) plots IDR against the city's average $\mathrm{IndDisc}_{ct}$ during 2007–10 across different prefecture cities; Panel (b) plots geographic heatmap of IDR for land allocation during 2007–10.

Finally, we combine the two subsidy policies and the alternative timing of residential tax cash flows, which results to an IDR for nontarget industries of 4.6%. Overall, future tax payment is quantitatively important when assessing land allocation efficiency.

#### 4.4.3 Geographic Variation in Land Misallocation

The national IDR masks significant heterogeneity in land allocation efficiency across cities. To assess land allocation efficiency at the city level, for each city $c$, we calculate $\mathrm{IDR}_c$ during 2007–10 as the discount rate $\rho$ that equates the average value of the LHS and RHS of the equation within the brace in Equation (5), also weighted by the size of land purchase by treated firms in city $c$ and year $\tau \in \{2007, 2008, 2009, 2010\}$.

Figure 5 plots geographic variation in $\mathrm{IDR}_c$. Panel (a) plots $\mathrm{IDR}_c$ against average industrial discount in 2007-10 and Panel (b) its geographic distribution. While cities with higher industrial discount have higher marginal industrial tax payment, their $\mathrm{IDR}_c$ is still typically lower than cities with lower industrial discount. The $\mathrm{IDR}_c$ negatively correlates with local GDP per capita, lower (higher) in coastal (inner) regions. Correlation between $\mathrm{IDR}_c$ and average GDP per capita during 2007–10 is $-0.36$.

Figure 5 has two important takeaways. First, while the national IDR is close to the firm discount rate, many cities undersupply or oversupply industrial land. The average $\mathrm{IDR}_c$ across

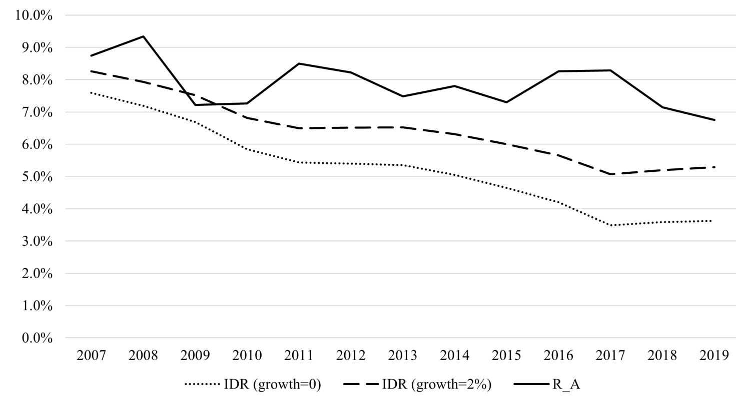



Figure 6: Time Series of IDR and Cost of Capital

Note: This figure plots the time series of IDR, assuming either zero or a 2% growth rate after 2024, as well as the average cost of capital for publicly listed industrial firms.

these 204 cities is 7.7%. Among them, 116 cities have an IDR lower than 8.0%, indicating oversupply of industrial and undersupply of residential land. Many are in coastal areas with more immigration and high house prices. These local governments can improve land allocation efficiency by allocating more land towards residential uses. In contrast, 88 cities have an IDR higher than 8.0%, indicating undersupply of industrial and oversupply of residential land. These cities are typically in interior areas with more emigration and relatively low house prices. These local governments can improve land allocation efficiency by reducing residential land allocations.

Second, the overall extent of land misallocation seems not very large in many cities. Among these 204 cities, 89 have an IDR between 7.0% and 9.0%, deviating from 8.0% by no more than 1%. The average absolute difference between $\mathrm{IDR}_c$ and 8.0% is about 1.3%. But this result needs to be taken with caution as measurement errors in the city-level industrial tax estimates can bias the overall dispersion of IDR. As this paper's primary goal is to emphasize the importance of taxes and empirically assess land misallocation, we will leave the quantitative evaluation of the welfare loss from land misallocation to future work, given there have already been many quantitative studies on this topic.

#### 4.4.4 Land Misallocation over Time

The IDR reported in Table 3 are based on land transactions in 2007–10, during which time we have high-quality data on industrial firms for our industrial tax estimation. Changes in land demand and government incentives may have moved IDR since 2010. To get some sense of how the land allocation efficiency has evolved over time, we assume Equation (18) also applies for $\tau > 2010$. We can then calculate the national $\mathrm{IDR}_\tau$ for each calendar year $\tau \geqslant 2007$.

Figure 6 reports the results. In the benchmark scenario assuming a zero growth rate of industrial tax payments after 2024, the estimated IDR decreased over time, and the gap between IDR and the firms' cost of capital, $R_A$, widened, meaning the industrial land has become increasingly oversupplied relative to residential land. This decreasing trend is not driven by the assumption of zero permanent growth rate – considering a permanent growth rate of 2% after 2024, we observe similar patterns as in Figure 6. Since 2007, house prices in China have increased dramatically. Our result suggests reallocating industrial land for residential use, at least in some cities, can be welfare improving.

# 5 Tax Benefits and Land Supply

The conceptual framework in Section 3 and the empirical exercise in Section 4 focus solely on the demand side of the land market. Note that Condition (4) is based on equilibrium variables—whether the equality holds or not depends on the government's land allocation decisions. In this section, we examine supply-side factors that influence these decisions.

## 5.1 The Supply Side of Land Allocation

It is *unclear* whether local governments systematically over- or undersupply industrial versus residential land relative to the Pareto-efficient level. Government benefits associated with land supply can be broadly categorized into nonpecuniary and pecuniary parts.

First, nonpecuniary benefits may include economic growth and employment, which local officials value due to either altruism or political incentives. Those that conclude an oversupply of industrial land based on the upfront industrial land discount often explain the oversupply with officials' growth-oriented incentives. However, residential land development can also generate immediate local output gains, particularly appealing to officials nearing the end of their terms. Thus, nonpecuniary incentives alone do not predict the direction of allocation bias.

Second, if local governments are price takers and maximize land allocation revenues (i.e., they act as usual suppliers in a competitive market), then Equation (4) will hold in equilibrium. Some deviations from this benchmark may favor residential over industrial land—e.g., myopic local officials or intergovernmental tax sharing could reduce the perceived long-term value of industrial tax benefits. Other deviations, such as local governments' market power in the residential land market, could lead to residential land rationing and a relative oversupply of industrial land. These competing forces lead to the observed variation in land allocation efficiency across locations.[19]

It remains unclear whether tax incentives affect local government land allocation decisions. The quantitative importance of future industrial tax payments and the fact that local governments impose official guidance on minimum tax payment on industrial land all imply that they do value future tax revenues when determining land allocations. To exploit this question, we investigate two key parameters governing local government tax incentives: the fraction of future industrial tax revenues local governments retain and their discount rate for those revenues. Because we do not have accurate time-varying estimates of IDR at the city level, we examine industrial discounts—strongly correlated with IDR as shown in Figure 5—as the outcome variable.

The literature on local officials' myopic behavior, particularly near the end of their terms, may leave the impression that such officials disregard long-term industrial tax revenues. We contend that this impression overlooks the stability of local governance system. In practice, grassroots-level local officials in China typically hold leadership positions for extended periods before concluding their political careers in a given locality. China's government personnel system is characterized by its hierarchical, step-by-step promotion structure: most officials begin at the local level and advance through the ranks, often within the same county. Among county party secretaries appointed between 2006 and 2010, roughly 45% had previously served as mayors of that county; 46% of county mayors were later promoted to party secretaries in that county. Since most party secretaries and mayors first hold deputy positions, their cumulative tenure in leadership roles within a county is often long enough to incentivize attention to long-term benefits.

### 5.2 Government Discount Rates

We conjecture that city governments with higher borrowing costs tend to supply residential rather than industrial land. We employ municipal corporate bond (MCB) yields as a measure of local government borrowing costs. MCBs are de facto municipal bonds widely used by local governments in China. To address the endogeneity concern that certain forces may affect both MCB yields and industrial discounts, we build on Chen et al. (2020) and use an instrumental variable for MCB yields related to China's RMB four-trillion stimulus plan in 2009.

[19] In Section A.2 in the appendix, we model the supply side of the land market with a most general specification about the local governments' objectives and formally show these results.

In response to the global financial crisis, the central government initiated a large fiscal stimulus plan involving additional fiscal spending of roughly four trillion RMB in 2009–10. Local governments responded by increasing investment in infrastructure, which had long-lasting effects on the local government's fiscal position and hence on future bond yields. The responsiveness of local officials depended on their tenure clock. Chen et al. (2020) show that cities in provinces whose governors were late in their term engaged in more local infrastructure investment in 2009, plausibly because the incentive to comply with the central government increases with the governor's term.[20]

Following Chen et al. (2020), we construct an instrument, $\mathtt{LateTerm}_c$ that equals one if city c's provincial governor had been in office for at least three years in the beginning of 2009 and zero otherwise. In the first stage, $\mathtt{LateTerm}_c$ is negatively correlated with MCB yield in subsequent years, in particular during 2012–19. This is consistent with greater infrastructure investment in 2009 leading to a stronger future fiscal position, for example in the form of greater values of land inventory with well-developed infrastructure and ready for sale or being used as collateral. The first stage is strong and statistically significant: the F-statistic for 2012–19 is 28.1.

The exclusion restriction is that these fiscal changes are only correlated with future industrial discounts through changes in MCB yields. In particular, the exclusion restriction requires that the governments' land inventory size, which is affected by $\mathtt{LateTerm}_c$, does not directly affect what mix of residential or industrial land is chosen for sale.[21] Moreover, Chen et al. (2020) show that thanks to the anticorruption campaign launched in 2012, there is negligible correlation between governor term in 2009 and in years after 2012. Thus, we apply the instrument to the sample starting from 2012 so that governor term in 2009 does not affect land allocation after 2012 through future governor terms.

We then instrument MCB yields by $\mathtt{LateTerm}_c$ and estimate the causal effect of MCB yield on industrial discounts, using the following specification:

$$\mathtt{IndDisc}_{c,t} = \beta \times \mathtt{MCBYield}_{c,t} + \sum_{\tau} \gamma_{\tau}' \cdot \mathbf{1}_{t=\tau} \cdot [X^1_{c,2008}, X^2_{c,t}] + \epsilon_{c,t}, \tag{25}$$

[20]More broadly, this is related to the literature on China's political economy that links local officials' promotion to their incentives of pursuing local economic growth during different stages of their terms (Ru, 2018). Moreover, the city government has a strong incentive to comply with its provincial governor's political agenda, because of China's "one-level-up" policy: local officials' promotions are largely determined by their immediate superior officials (Chen and Kung, 2019).

[21]Chen et al. (2020) show that provinces with greater stimulus bank loans in 2009 experienced faster MCB growth and more shadow banking activities during 2012–15 due to refinancing. Chen et al. (2020) are concerned with a pure quantity implication, while the price implication of 2009 stimulus bank loans on future MCB yields is ambiguous, exactly because of the expanded land inventory mentioned here.

where $\mathsf{MCBYield}_{c,t}$ is the average yield of MCB bonds issued by city $c$ in year $t$ and weighted by issuance amounts.[22] To avoid potential direct effect of the governor's term in 2009, we estimate Eq. (25) based on the sample period 2012–19. We control for time-varying effects of two sets of city-level economic conditions: the first contains ex ante measures, $X^1_{c,2008}$, which include GDP per capita, the growth rate of GDP from the previous year, and the fiscal deficit over GDP, all measured in the year 2008; the second contains ex post measures, $X^2_{c,t}$, which include the growth of GDP, land price, and industrial output from 2008 to year $t$. The ex post conditions are included to control potential channels through which $\mathsf{LateTerm}_c$ might affect the outcome variable and hence invalidate the exclusion restrictions.

Table 4 shows the results. The first three columns of Panel A show OLS estimation results; consistent with our conjecture, industrial discounts are negatively correlated with MCB yields in the cross section. In Columns (4) and (5), we instrument $\mathsf{MCBYield}_{c,t}$ with $\mathsf{Lateterm}_c$; the effect of $\mathsf{MCBYield}_{c,t}$ is negative and significant. In Column (6), when including the ex post conditions as controls, the IV coefficient estimate barely changes.

In Panel B, we test whether MCB yields also affect the *quantities* of residential and industrial land sold, by replacing the dependent variable in Eq. (25) with the difference between industrial and residential land supply per capita. In line with our hypothesis, when MCB yields are higher, residential land sold per capita increases, industrial land sold per capita decreases (though insignificantly), and the difference between industrial and residential land sold per capita decreases. When MCB yield increases by 1%, annual industrial relative to residential land supply will decrease by 0.5 square meter per capita.

Our findings imply that city governments' land allocations are entangled with their financial strength. Given the key role of land allocation on industry structure (e.g., the relative size of real estate and manufacturing sector), policy makers should consider the knock-on effect on industrial structure when initiating policies about municipal finance.

### 5.3 City Tax Shares

City governments retain most land sales revenue, but share value-added, corporate income and business taxes with upper-level governments. The central government gets a uniform share

[22] The common definition of MCBs is given by Wind (Chen et al., 2020), of which the sample size is quite limited before 2010. Our sample includes MCBs either defined by Wind or ever included in the calculation of ChinaBond Urban Construction Investment Bond Yield-to-Maturity Curve.

Table 4: Industrial Discount and Municipal Corporate Bond Yield

Panel A: Effect on Industrial Land Discount

| Specification | OLS | OLS | OLS | IV | IV | IV |
|---|---|---|---|---|---|---|
| Dep Var: IndDisc | (1) | (2) | (3) | (4) | (5) | (6) |
| MCBYield, % | -892.0*** | -529.6*** | -401.8*** | -2,946*** | -4,263*** | -4,394** |
| | (-9.422) | (-6.319) | (-5.592) | (-7.502) | (-3.047) | (-2.581) |
| Ex ante Controls | No | Yes | Yes | No | Yes | Yes |
| Ex post Controls | No | No | Yes | No | No | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,547 | 1,543 | 1,541 | 1,547 | 1,543 | 1,541 |
| R-squared | 0.328 | 0.457 | 0.559 | -0.954 | -2.573 | -2.607 |
| #City | 277 | 276 | 276 | 277 | 276 | 276 |
| F statistic | | | | 32.68 | 8.024 | 6.945 |

Panel B: Effect on Industrial versus Residential Land Supply

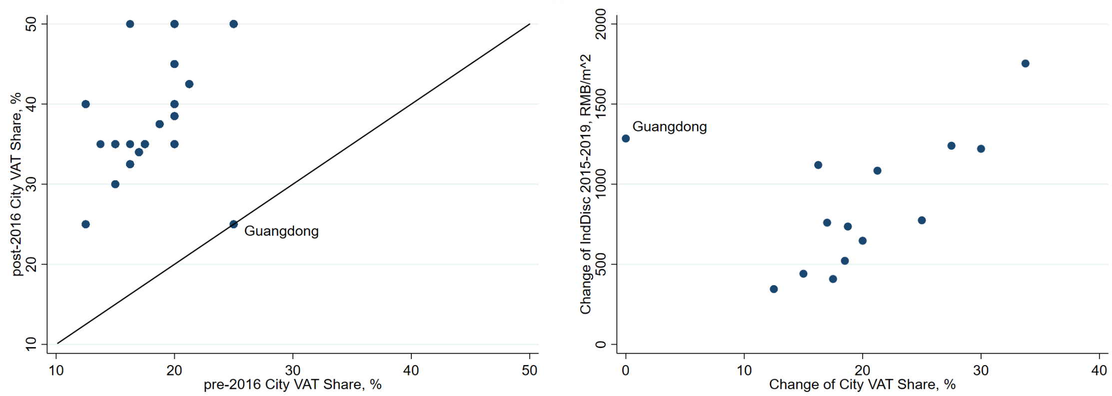
| Dep Var: | (Ind-Res)/Pop | Ind/Pop | Res/Pop |
|---|---|---|---|
| | (1) | (2) | (3) |
| MCBYield, % | -50.44** | -23.44 | 25.31** |
| | (-2.287) | (-0.986) | (2.193) |
| Ex ante Controls | Yes | Yes | Yes |
| Ex post Controls | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 1,629 | 1,629 | 1,629 |
| R-squared | -0.027 | 0.070 | -0.292 |
| #City | 298 | 298 | 298 |
| F statistic | 30.30 | 30.30 | 30.30 |

Note: This table shows the effect of City MCB yields on industrial land discount (Panel A) and the industrial relative to residential land supply in square meters per 100 people (Panel B). The sample period is from 2012–19. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of value-added taxes. The province-level governments split the remainder between itself and city-level governments, with variations in the share of VAT accrued to city governments across different provinces.[23] Although local governments may partially internalize tax revenues accruing to upper level governments, they should prioritize their own retained share of tax revenues. We conjecture that a higher share of value-added taxes city governments retain would lead to higher industrial discounts and more industrial relative to residential land supply.

For identification, we analyze a change in tax-sharing schemes in 2016. Before May 1, 2016, the

[23] Wu and Zhou (2015) show that the city government VAT share tends to be higher if there is less variation in economic development across cities in the province, if the city's industrial sector is more developed, and if there are fewer state-owned firms controlled by the province governments.




(a) City VAT Share Pre- and Post-2016 (b) Change in Ind. Discount vs VAT Share

Figure 7: Change of City VAT Share and Industrial Land Discount

Notes: Panel (a) plots the city government's share of VAT before and after 2016. Panel (b) is a binscatter of the change in industrial land discount from 2015 to 2019 against the change in city VAT share across cities.

central government took 75% of value-added taxes; the remaining 25% went to provincial and city governments. On May 1, 2016, Beijing launched a major tax code change—the so-called "Business to Value-Added" program—enlarging the coverage of value-added taxes. This reform modified the tax-sharing scheme, so that the share of value-add taxes retained by local governments increased from 25% to 50%.[24] Provincial governments can determine how to split the incremental 25% of the value-added taxes between itself and city governments. The differential increase in the city's VAT share in 2016 provides an opportunity to test the effect of tax sharing on the industrial discounts.

**Raw Data.** Panel A in Figure 7 shows the pre-2016 versus post-2016 city VAT share. Most cities experienced an increase in their share, except cities in Guangdong whose share remained at 25%; we explain the special circumstance of Guangdong below. The size of the tax share increase varies substantially across cities. Panel B in Figure 7 is a binned scatterplot of the change in industrial land discount from 2015 to 2019 relative to the city VAT share change in 2016. Consistently with our conjecture, the two variables have a strong positive correlation (excluding cities in Guangdong).

In both panels of Figure 7, cities in Guangdong province seem to be outliers. Although they experienced zero increase in their share of VAT, the industrial land discount increased substantially from 2015 to 2019 in these cities. One possible explanation is that Guangdong implemented

[24]Local governments previously received the entirety of business taxes. After the launch of this program in May 2016, business taxes were replaced by value-added taxes and shared by the central government, who further increased the VAT share of the local governments to keep their fiscal revenue stable.

Table 5: City VAT Share and Industrial Land Discount

| | | Price | | | Quantity | | |
|---|---|---|---|---|---|---|---|
| Dep Var: | | IndDisc | $P_R$ | $P_I$ | (Ind-Res)/Pop | Res/Pop | Ind/Pop |
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta VATShare\times$ | | | | | | | |
| Year= | 2012 | -2.332 | -3.956 | -1.624 | 1.618 | 0.0805 | -0.828 |
| | | (-0.171) | (-0.307) | (-0.844) | (1.484) | (0.128) | (-0.449) |
| | 2013 | -10.88 | -11.32 | -0.446 | 0.954 | 0.875 | 0.906 |
| | | (-0.999) | (-1.041) | (-0.412) | (0.924) | (1.349) | (0.709) |
| | 2014 | 0.691 | 1.379 | 0.688 | -0.296 | 0.342 | -1.255 |
| | | (0.0366) | (0.0721) | (0.693) | (-0.387) | (0.908) | (-1.083) |
| | 2016 | 26.99*** | 25.46** | -1.533** | 0.0419 | -0.640 | -0.761 |
| | | (2.717) | (2.553) | (-2.268) | (0.0607) | (-1.634) | (-1.005) |
| | 2017 | 60.75*** | 58.71*** | -2.050** | 1.470* | 0.798 | 2.416** |
| | | (3.954) | (3.772) | (-2.446) | (1.762) | (1.456) | (2.345) |
| | 2018 | 39.58** | 38.13** | -1.455 | 4.001*** | 0.231 | 4.057*** |
| | | (2.264) | (2.157) | (-1.023) | (3.679) | (0.378) | (3.311) |
| | 2019 | 55.08*** | 54.80*** | -0.286 | 0.968 | 0.174 | 0.0822 |
| | | (3.367) | (3.315) | (-0.210) | (0.976) | (0.327) | (0.0626) |
| Year FE | | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | 2,062 | 2,062 | 2,062 | 2,217 | 2,217 | 2,217 |
| R-squared | | 0.836 | 0.847 | 0.825 | 0.705 | 0.650 | 0.664 |
| #City | | 258 | 258 | 258 | 280 | 280 | 280 |

Note: This table shows how the change in city VAT share affects industrial land discounts and the industrial versus residential land supply. The sample consists of all the municipal cities (except those in Guangdong); the sample size in Column (1)–(3) is smaller because we need industrial discount estimates from 2012–19. The treatment variable, $\Delta VATShare$, is in percentage and the land supply is square meters per 100 people. Standard errors are clustered by cities. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

confounding policies that encouraged industrial land supply, and these policies did not exist in other provinces. We provide detailed discussion on these unique land-related policies for Guangdong in Online Appendix C.1. As such, we remove Guangdong from the remainder of this section's analysis.

**Event Study.** We apply an event study analysis to leverage the change in tax-sharing schemes in 2016:

$$y_{c,t} = \alpha_c + \gamma_t + \sum_{\tau\neq 2015} \beta_\tau \times \mathbf{1}_{t=\tau} \times \Delta VATShare_c + \varepsilon_{c,t}. \tag{26}$$

In Eq. (26), the base year is 2015, the year before the taxation change, and $\Delta VATShare_c$ is the change in city's VAT share in 2016.

Table 5 reports the estimation results. Consistently with our conjecture, we observe a significant and positive treatment effect on the industrial discount since 2016. Moreover, there was no significant difference between cities with differential treatment before 2016, supporting the parallel trends assumption for DID estimation.

In Columns (2)–(3), we study industrial and residential land prices separately. Consistent with our framework, as a greater share of industrial tax revenues accrue to the local government, residential land prices tend to increase and industrial land prices to decrease. The effect on residential land prices is quantitatively larger, likely because such price levels are much higher.

In Columns (4)–(6) of Table 5, we examine the quantities of industrial and residential land supply, by replacing the dependent variable in Eq. (26) with the difference between industrial and residential land supply per capita. In Column (4), consistent with the first hypothesis, an increase in city government tax share shifts the land supply towards industrial relative to residential uses. In Column (5)–(6), we observe that local governments experiencing a higher increase in their VAT share immediately cut residential land supply and increase industrial supply over the two years following the policy change.

We have stronger evidence on price than on quantity. The industrial discount can adjust through two mechanisms. First, since the government and potential buyers negotiate transaction prices, buyers who know more future taxes go to the local government may request a greater industrial discount; no quantity adjustment is even required in this case. Second, and perhaps more important, as mentioned in Section 2, the quantity adjustment may not occur in the short run given planning constraints. But, as land is a durable good, forward-looking prices (and hence industrial discounts) will immediately adjust.

## 6 Conclusion

As land is one of the most important economic resources, its misallocation across different uses can generate significant welfare loss. We provide a model-free assessment of land allocation efficiency in China. We emphasize that given the differential tax profile of land across uses, it is both theoretically and quantitatively important to include the associated tax payment and the direct cost of land purchase when evaluating firms' marginal willingness to pay for different types of land. Our exercise reveals significant variation in land allocation efficiency across China. Cities with greater population, immigration, and house prices could benefit from reallocating industrial land to residential use; those with lower house prices could benefit from the opposite reallocation.

Our results also have implications for understanding land price drivers in China and how they are linked to government incentives, like intergovernmental tax sharing and local governments' intertemporal revenue trade-offs. From the central government's perspective, the tax sharing scheme between central and local governments can be designed to counteract effects of other forces, like local governments' market powers in the local land market and the pursuit of nonpecuniary benefits associated with the land supply, to achieve desired land allocation outcomes.

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# Online Appendix

## A Model Appendix

### A.1 The Condition for Land Allocation Efficiency

**Definition 2.** A feasible allocation is given by $\{y_j, x_j, L_{jI}, L_{jR}\}$ such as: (1) $(y_j, L_{jI}, L_{jR})$ is compatible with the production technology; (2) $\sum_i c_i = \sum_j y_j$; and (3) $\sum_j L_{jI} + \sum_j L_{jR} = \overline{L}$.

**Proof of Proposition 1.**

*Proof.* Profit maximization by all firms in competitive equilibrium implies that the LHS of Equation (4) does not vary with $k$ and the RHS does not vary with $\ell$. So, we only need to show the equality.

To show Equation (4) is a sufficient condition, suppose there is an alternative feasible allocation $\{y_j, x_j, L_{jI}, L_{jR}\}$ that Pareto dominates the competitive equilibrium, i.e., $c_i \succsim c_i^\star$ $\forall i$ and $c_i \succ c_i^\star$ for some $i$. Because consumer preference is locally non-satiated, it follows that

$$P^\star \cdot c_i \geqslant P^\star \cdot \omega_i + \sum_j \theta_{ij}\pi_j^\star + \theta_i\Big(\sum_{j\in\mathcal{I}}(\tau P^\star \cdot y_j^\star + P_I^\star \cdot L_{jI}^\star) + \sum_{j\in\mathcal{R}}(\tau(P^\star \cdot y_j^\star - P_R^\star \cdot L_{jR}^\star) + P_R^\star \cdot L_{jR}^\star)\Big),$$

with $>$ for some $i$. Sum across all the consumers, we then have

$$\sum_i P^\star \cdot c_i > \sum_i P^\star \cdot \omega_i + \sum_j P^\star y_j^\star \tag{27}$$

Firm's profit maximization implies:

$$P^\star y_j(1-\tau) - P_I^\star L_{jI} \leqslant P^\star y_j^\star(1-\tau) - P_I^\star L_{jI}^\star, \forall j \in \mathcal{I}$$
$$(P^\star y_j - P_R^\star L_{jR})(1-\tau) \leqslant (P^\star y_j^\star - P_R^\star L_{jR}^\star)(1-\tau), \forall j \in \mathcal{R}$$

Sum across all the firms, we have

$$\begin{aligned}
&\sum_j P^\star y_j - \Big[\sum_{j\in\mathcal{I}}(\tau P^\star y_j + P_I^\star L_{jI}) + \sum_{j\in\mathcal{R}}(\tau(P^\star y_j - P_R^\star L_{jR}) + P_R^\star L_{jR})\Big] \\
<&\sum_j P^\star y_j^\star - \Big[\sum_{j\in\mathcal{I}}(\tau P^\star y_j^\star + P_I^\star L_{jI}^\star) + \sum_{j\in\mathcal{R}}(\tau(P^\star y_j^\star - P_R^\star L_{jR}^\star) + P_R^\star L_{jR}^\star)\Big]
\end{aligned} \tag{28}$$

Because $P^\star \cdot y_j(L_{jI}; P^\star)$ increasing and weakly concave in $L_{jI}$, it follows that

$$\sum_{j\in\mathcal{I}} \tau P^\star y_j \leqslant \sum_{j\in\mathcal{I}} \tau P^\star y_j(\hat{L}_{jI}; P^\star),$$

where $\hat{L}_{jI}$ is such that $Y'(\hat{L}_{jI}; P^\star)$ is constant across all $j \in \mathcal{I}$ and $\sum_{j\in\mathcal{I}} \hat{L}_{jI} = \sum_{j\in\mathcal{I}} L_{jI}$.

Denote the LHS and RHS of Equation (4) as $MPL$. Without loss of generosity, assume

$\sum_{j\in\mathcal{I}} L_{jI} \leqslant \sum_{j\in\mathcal{I}} L^\star_{jI}$ and $\sum_{j\in\mathcal{R}} L_{jR} \geqslant \sum_{j\in\mathcal{R}} L^\star_{jR}$. We then have

$$\begin{aligned}
\sum_{j\in\mathcal{I}} \tau P^\star y_j + P^\star_I L_{jI} &\leqslant \sum_{j\in\mathcal{I}} \tau P^\star y_j(\hat{L}_{jI}; P^\star) + P^\star_I L_{jI} \\
&\leqslant \sum_{j\in\mathcal{I}} \tau P^\star y^\star_j - \tau Y'(L^\star_{jI}; P^\star)\cdot(L^\star_{jI} - \hat{L}_{jI}) + P^\star_I L_{jI} \\
&= \sum_{j\in\mathcal{I}} \tau P^\star y^\star_j - MPL\cdot(L^\star_I - L_I) + P^\star_I L^\star_I
\end{aligned} \tag{29}$$

Similarly, we also have

$$\begin{aligned}
\sum_{j\in\mathcal{R}} \tau(P^\star y_j - P^\star_R L_{jR}) + P^\star_R L_{jR} &\leqslant \sum_{j\in\mathcal{R}} \tau(P^\star y_j(\hat{L}_{jR}; P^\star) - P^\star_R L_{jR}) + P^\star_R L_{jR} \\
&\leqslant \sum_{j\in\mathcal{R}} \tau P^\star y^\star_j + \tau Y'(L^\star_{jR}; P^\star)\cdot(L_{jR} - \hat{L}^\star_{jR}) + (1-\tau)P^\star_R L_{jR} \\
&= \sum_{j\in\mathcal{R}} \tau P^\star y^\star_j + MPL\cdot(L_R - L^\star_R) + (1-\tau)P^\star_R L^\star_R
\end{aligned} \tag{30}$$

Combine Inequality (28), (29) and (30), we have

$$\sum_j P^\star y_j < \sum_j P^\star y^\star_j$$

This condition contracts with Inequality (27) because $\sum_j y_j = \sum_i (c_i - \omega_i)$. Therefore, there does not exist such a feasible allocation that Pareto dominates the competitive equilibrium.

To show Equation (4) is a necessary condition, suppose it does not hold. Without loss of generosity, assume

$$\tau Y'(L^\star_{kI}; P^\star) + P^\star_I > \tau(Y'(L^\star_{\ell R}; P^\star) - P^\star_R) + P^\star_R$$

Firm's profit maximization implies:

$$\begin{aligned}
Y'(L^\star_{kI}; P^\star) - (\tau Y'(L^\star_{kI}; P^\star) + P^\star_I) = 0 \\
Y'(L^\star_{\ell R}; P^\star) - (\tau(Y'(L^\star_{\ell R}; P^\star) - P^\star_R) + P^\star_R) = 0
\end{aligned}$$

Therefore, $Y'(L^\star_{kI}; P^\star) > Y'(L^\star_{\ell R}; P^\star)$. Now, consider such a marginal reallocation of land for any arbitrary firms:

$$(L^\star_{kI}, L^\star_{\ell R}) \to (L^\star_{kI} + \varepsilon, L^\star_{\ell R} - \varepsilon).$$

The resulting change of output is $(y'_k(L_{kI}) - y'_\ell(L_{\ell R}))\varepsilon$. Adjust the equilibrium $c^\star_i$ of consumer $i$ by this change of output, and his utility will change by:

$$u'_i(c^\star_i)\cdot(y'_k(L_{kI}) - y'_\ell(L_{\ell R}))\varepsilon \propto P^\star\cdot(y'_k(L_{kI}) - y'_\ell(L_{\ell R})) = Y'(L^\star_{kI}; P^\star) - Y'(L^\star_{\ell R}; P^\star) > 0$$

That is, the consumer $i$ is strictly better off with this change of consumption. Therefore, the competitive equilibrium is not Pareto efficient when Equation (4) fails. $\square$

## A.2 A Model of Government Land Allocation

**Setup.** The government allocates a fixed amount of land inventory $\overline{L}$ between residential use $L_R$ and industrial use $L_I$. For simplicity, we will abstract from the industrial production and residential development process and market demand structure, and denote the value-added or profit of the industrial sector by $f(L_I)$ and the residential sector by $g(L_R) - P_R \cdot L_R$. Note that land is counted as capital for the industrial sector and intermediate input for the residential sector. $f(L_I)$ occurs annually while $g(L_R) - P_R \cdot L_R$ occurs only once. Assume both $f(L_I)$ and $g(L_R)$ are twice differentiable, increasing and concave.

We consider a very general specification of the local governments' objective function, which includes three components. The first is land sale revenues, $P_I \cdot L_I$ and $P_R \cdot L_R$. The second is tax revenues. Denote the effective tax rate by $\tau_R$ ($\tau_I$) and the share that is internalized by the local governments by $\kappa_R$ ($\kappa_I$) for the residential (industrial) taxes. Partial internalization of tax revenues arises due to the intergovernmental tax sharing. The effective tax revenues from residential development internalized by the local governments is then $\kappa_R \cdot \tau_R \cdot (g(L_R) - P_R \cdot L_R)$, which occurs only once. The effective industrial tax revenues, $\kappa_I \cdot \tau_I \cdot f(L_I)$, is a perpetuity. In order to capture the myopia of local officials, we assume that in each period there is a probability $1 - \delta$ that the official in charge will leave office and do not care about the tax revenues going forward. Denote the local government discount rate by $R_g$. The present value of the future industrial tax revenues internalized by the myopic local official is then

$$\kappa_I \cdot \tau_I \cdot f(L_I) \sum_{t \geqslant 1} \left(\frac{\delta}{1 + R_g}\right)^t = \kappa_I \cdot \tau_I \cdot f(L_I) \frac{\delta}{1 + R_g - \delta}$$

The last component is the non-pecuniary benefits arising from economic growth and employment increase. As the industrial and residential development can generate quite different effect on economic growth and employment, we assume the non-pecuniary benefit is $\lambda_I \cdot f(L_I)$ from industrial and $\lambda_R \cdot (g(L_R) - P_R \cdot L_R)$ from residential land supply.

On the demand side, we assume competitive market demand and constant price elasticity of demand, $\sigma_R$ and $\sigma_I$.

As in Section 3, we define IDR of industrial land supply to be the discount rate that will equate the present value of cash flows between the marginal industrial and marginal residential land supply. In this framework, it will be

$$\text{IDR} \equiv \frac{\tau_I \cdot f'(L_I)}{\tau_R(g'(L_R) - P_R) + P_R - P_I}$$

The numerator is the perpetuity marginal tax revenues from industrial land, and the denominator is the marginal tax revenues from residential land plus the industrial discount. Denote the firms' discount rate by $R_f$. By Proposition 1, the competitive equilibrium is Pareto efficient if and only if $\text{IDR} = R_f$.

**Market Equilibrium.** To characterize the market equilibrium, consider the local governments' optimization problem:

$$\max_{L_I, L_R} \underbrace{L_I P_I + L_R P_R}_{\text{Land Sale Revenues}} + \underbrace{\kappa_I \tau_I \frac{\delta}{1+R_g-\delta} f(L_I) + \kappa_R \tau_R (g(L_R) - L_R P_R)}_{\text{Tax Revenues}} + \underbrace{\lambda_I f(L_I) + \lambda_R (g(L_R) - L_R P_R)}_{\text{Non-pecuniary Benefit}}$$

$$\text{s.t. } L_I + L_R = \overline{L},\ g'(L_R) = P_R,\ f'(L_I) \cdot \frac{1-\tau_I}{R_f} = P_I \tag{31}$$

The first condition is the constraint on the total land supply. The other two constraints represent competitive demand for residential and industrial land. That is, the marginal post-tax profit should be zero when the land demand is competitive.

Substitute the three conditions into the objective function, we can write the objective function as $W(L_I)$. The first order derivative of $W(L_I)$ is then

$$W'(L_I) = \big(\frac{\delta}{1+R_g-\delta}\kappa_I \tau_I + \lambda_I + \frac{1-\tau_I}{R_f}(1-\sigma_I^{-1})\big) f'(L_I) - \big(1 - \sigma_R^{-1}(1-\kappa_R\tau_R - \lambda_R)\big) g'(L_R) \tag{32}$$

The government optimal choice of $L_I$ is then given by $W'(L_I^\star) = 0$.

**Proposition 2.** *When the local governments (1) internalize all the tax revenues ($\kappa_I = \kappa_R = 1$), (2) are not myopic ($\delta = 1$), (3) do not care about non-pecuniary benefits ($\lambda_I = \lambda_R = 0$), (4) have the same discount rate as firms ($R_g = R_f$), (5) and possess no market power in the land markets ($\sigma_R = \sigma_I = \infty$), then in equilibrium,* $\text{IDR}^\star = R_f$.

*Proof.* Plug the parameters into Eq. (32), we get $\frac{f'(L_I^\star)}{R_g} = g'(L_R^\star)$. Plug this condition and $g'(L_R) = P_R$, $f'(L_I) \cdot \frac{1-\tau_I}{R_f} = P_I$ into the definition of IDR, we get $\text{IDR}^\star = R_f$. □

Proposition 2 says that when there are no market frictions, i.e., the local officials internalizes all the tax revenues generated from their land supply, are not myopic, only care about the pecuniary benefits, discount the future similarly as firms, and do not have market power over local land market, the market equilibrium will feature efficient land allocation. Under these conditions, the local governments act no differently from a usual firm except the way they collect payment from the buyers (i.e., land price plus tax revenues). Of course, these conditions are likely to be violated in practice. Importantly, the violation of some of these assumptions will lead to more industrial land supply, while others will lead to the opposite. As a result, it is uncertain whether the market equilibrium features under- or over-supply of industrial land.

**Proposition 3.** $L_I^\star$ *will increase and* $\text{IDR}^\star$ *will decrease when* $\lambda_I$ *increases and* $\sigma_R$ *decreases;* $L_I^\star$ *will decrease and* $\text{IDR}^\star$ *will increase when* $\delta$ *decreases,* $\kappa_I$ *decreases,* $R_g$ *increases,* $\sigma_I$ *decreases and* $\lambda_R$ *increases.*

Proposition 3 states how the equilibrium land allocation and IDR would change under potential deviations from the benchmark scenario in Proposition 2. Specifically, industrial land will be over-supplied when the local governments care about the long-run industrial growth, or when they have large market power in the residential land market which leads to rationing of residential land supply. Alternatively, industrial land can be under-supplied when the local officials are myopic, when there is intergovernmental sharing of industrial taxes, when the local governments are in financial distress, have market power in the industrial land market, or value economic gains from residential development. In equilibrium, depending on these competing forces, it is uncertain whether the industrial land is under- or over-supplied.

**Proof of Proposition 2.**

*Proof.* Plug the parameters into Eq. (32), we get $\frac{f'(L_I^\star)}{R_g} = g'(L_R^\star)$. Plug this condition and $g'(L_R) = P_R$, $f'(L_I) \cdot \frac{1-\tau_I}{R_f} = P_I$ into the definition of IDR, we get $IDR^\star = R_f$. □

*Proof.* As $f(L_I)$ and $g(L_R)$ are increasing and concave, $W'(L_I)$ is non-increasing in $L_I$. The proposition then follows as the parameters shift $W'(L_I)$ downward or upward. □

# B Supplementary Materials for Section 4

## B.1 Data Cleaning

**Land data.** Our land sale data is from the Ministry of Natural Resources. We adopt the following procedures to remove outliers. First, the recorded size of a number of land parcels is above 10 million square meters, which are probably errors. We correct it by dividing the size by 10,000, the standard multiplier in Chinese unit systems. Second, the recorded price of some land parcels is over 100,000 yuan per square meter, which are also errors. Similarly, we scale the price down by 10,000.

We retrieve geographical coordinates of each land parcel by inputting their street addresses into the Gaode maps API. To verify the accuracy of the retrieved coordinates, we collect the Gaode address corresponding to the retrieved coordinates and compare it with the raw address in the land-sale data. We keep lands for which the Gaode address and the raw address are in the same town.

**Firm data.** Our firm data is from the ASIF database, collected by the Chinese National Bureau of Statistics. There is no consistent firm identifier in the ASIF database that is non-missing in all years. We thus rely on firm names to match firms across years. The database is censored from below, in the sense that one industrial firm will enter the database only in years when its annual sales exceeds a certain threshold, and if in the next year its annual sales fall below the threshold, it will not be in the database for that year. We can lose track of a firm in the ASIF database not only due to censoring, but also to other reasons such as the data collecting process or changing firm names. We discuss the potential bias of censoring in appendix B.5.

Table A.1: Summary Statistics of Industrial Lands and Land Buying Firms

| | Obs | Mean | Std Dev | Obs | Mean | Std Dev |
|---|---|---|---|---|---|---|
| ***A. Industrial Lands Characteristics*** | Sample, 2007-2010 | | | Population, 2007-2010 | | |
| Land price per square meter (yuan) | 22,566 | 207.74 | 217.96 | 122,901 | 180.77 | 284.72 |
| Area (1,000 $m^2$) | 22,636 | 38.16 | 50.23 | 124,340 | 39.04 | 103.88 |
| Distance to urban unit centers (km) | 22,636 | 10.69 | 9.9 | 124,341 | 10.92 | 11.29 |
| | | | | | | |
| ***B. Firm Characteristics*** | Merged Firms, 2003-2013 | | | All Firms, 2003-2013 | | |
| Sales revenue | 70,466 | 260.4 | 1,206.591 | 2,151,097 | 178.87 | 1,626.65 |
| Sales cost | 70,464 | 222.75 | 1,085.41 | 2,150,925 | 151.88 | 2,141.12 |
| Total assets | 70,462 | 210.89 | 1,221.79 | 2,151,003 | 151.74 | 2,113.02 |
| Gross value of industrial output | 70,326 | 264.85 | 1,126.2 | 2,148,079 | 179.89 | 1,543.06 |
| Enterprise income tax | 60,334 | 2.75 | 36.92 | 1,969,737 | 1.9 | 38.38 |
| Value-added tax | 68,429 | 7.58 | 53.34 | 2,115,965 | 5.9 | 89.94 |
| Sales tax and surtax | 68,603 | 1.84 | 32.06 | 2,122,431 | 2.72 | 146.12 |
| Total profit | 70,345 | 16.71 | 91.4 | 2,149,174 | 11.91 | 269.09 |
| Sales value | 70,320 | 258.65 | 1,118.07 | 2,147,941 | 178.28 | 3,469.36 |
| Average annual number of employees | 69,288 | 363.05 | 1,437.91 | 2,124,366 | 287.57 | 7,841.25 |

Panel A is summary statistics of the sample and population of industrial land parcels sold during 2007-2010. Panel B is summary statistics of firm-year (2003-2013) observations in our sample of merged firms that purchased land during 2007-2010 and in the population of all ASIF firms. In total, there are 19,602 unique merged firms that purchased land during 2007-2010 and 711,023 unique ASIF firms between 2003-2013. All variables except the last one in Panel 2 are measured in one million yuan.

**Merging.** We merge the land-sale data with firm data by the name of land buyers. We merge not only land parcels directly bought by the firm, but also those bought by the firm's immediate controlling subsidiaries (ICS), and the ICSs of the firm's ICSs, and so forth. We define firm A as firm B's ICS if firm B has at least a 50% equity share in firm A. The ownership data come from firm registry information covering the universe of firms in China. Table A.1 shows how the merged sample compares to the full samples of land parcels and firms.

## B.2 Constructing Urban Units

Cities are a relatively large unit of geography, and cities may have multiple clusters of developed land with different prices. To account for this possibility, we divide cities into "urban units." To do this, we use geographic data from Liu et al. (2018), who use Google Earth images to classify 30m×30m cells as urban or non-urban land, where urban land refers to an impervious surface such as pavement, concrete, brick, stone and other man-made impenetrable cover types. We then cluster urban land into contiguous blocks, using the ArcGIS function arcpy.AggregatePolygons_cartography. Essentially, this function produces blocks of land, iteratively connecting blocks to form larger blocks, as long as they are within a specified distance of each other. The function has two parameter settings: the maximum permitted separation distance between units, which we set as one mile, and the maximum area of holes to fill, which we set as

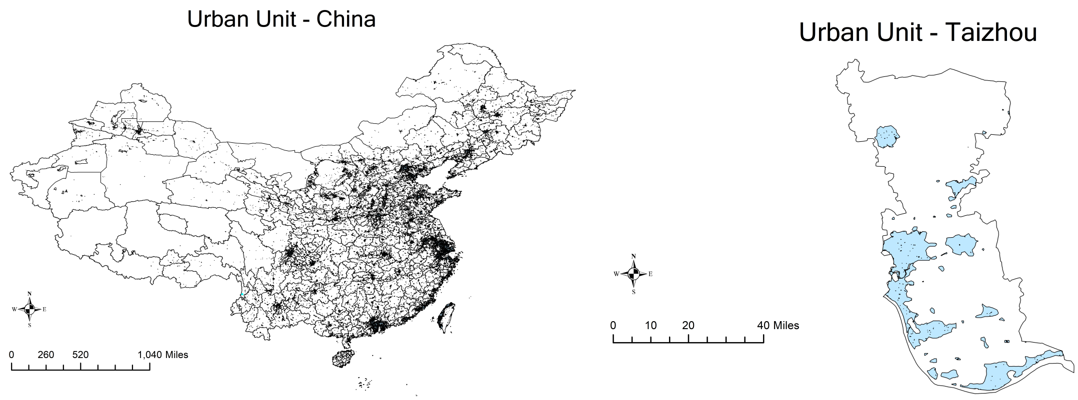



Figure A.1: Examples of Urban Units.

Note: Panel A is the distribution of all urban units in China. Panel B illustrates the urban units with the city of Taizhou. Each blue polygon with black outline represents one urban unit.

one square mile. We keep urban units of size bigger than one square mile, extract their centroids, and map each land parcel to the closest urban area centroid.

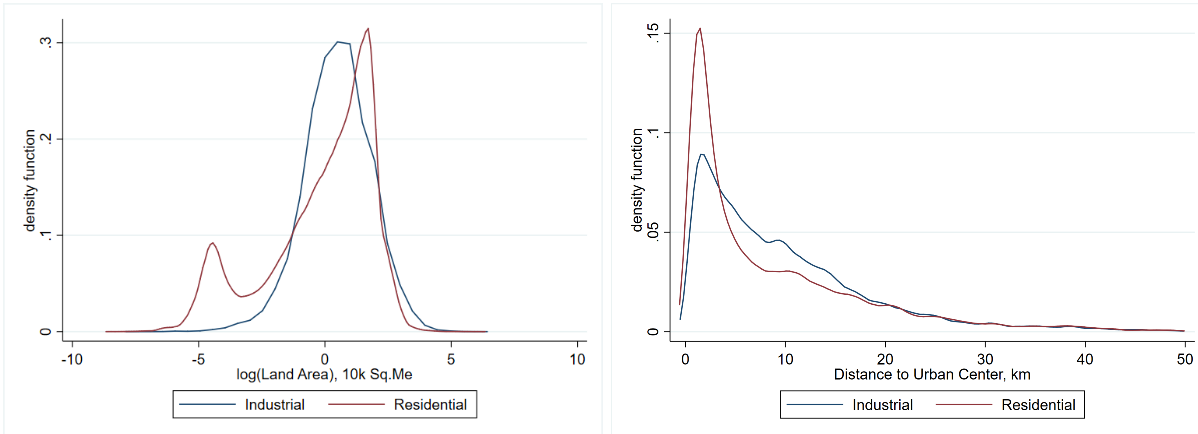
In Figure A.1, we first show the distribution of urban units throughout the country. A larger fraction of land is covered by these urban units in the more developed coastal areas, especially the Circum-Bohai Sea Region, the Yangtze River delta, and the Pearl River Delta. In Panel B we use Taizhou, a medium-sized city in Jiangsu, as an example to show the urban units. Each blue polygon with a black outline represents one urban unit.

There are 21,048 different urban units across the country. The median and mean of the total number of urban units in each prefecture city is 44 and 57, respectively. The median size of the urban units is 0.51 square kilometers and the mean is 8.39 square kilometers.

We match each land parcel to the nearest urban unit. In our estimation of industrial land discount, we use all the residential and industrial land parcels sold through auction during 2007-2019, and we impose an additional restriction to the sample size in terms of the number of land sales in each prefecture city. This leaves us with 3,837 different urban units, and the mean and median number of land parcels matched to these 3,837 urban units are 173 and 92, respectively. The mean and median size of these 3,837 urban units are 11.57 square kilometers and 0.52 square kilometers.

### B.3 Land Characteristics: Industrial versus Residential

Figure A.2 shows that the distribution of land characteristics for industrial land has similar support to that for residential land. Figure A.3 shows the distribution of the R-squared of the pricing functions (6) and (8) across different city-period samples.

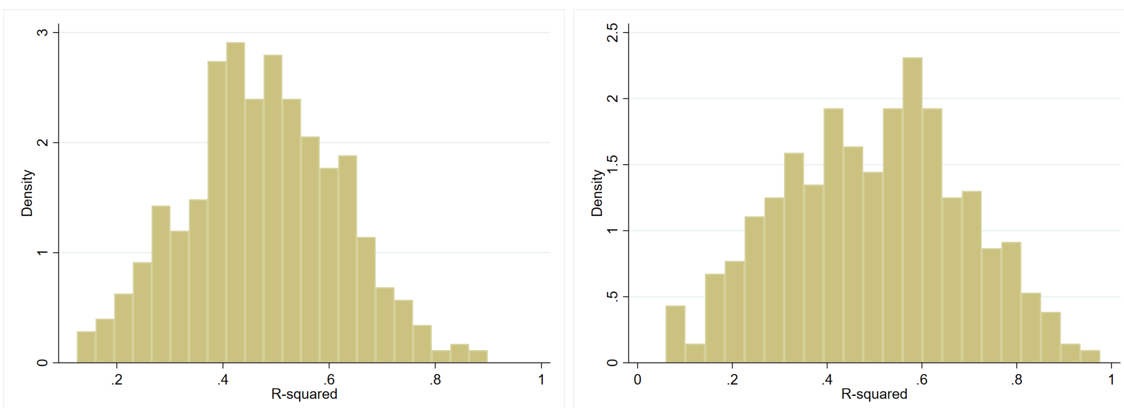



(a) Land Area

(b) Distance to Urban Center

Figure A.2: Land Characteristics: Industrial versus Residential

Note: These two graphs show the distribution of land area (Panel (a)) and the distance of the land to the urban center (Panel (b)) for industrial and residential land parcels separately.




(a) Residential

(b) Industrial

Figure A.3: Performance of the Land Pricing Model

Note: These two graphs show the distribution of R-squared of the two pricing functions, (6) and (8), across different samples defined by city-period combinations.

## B.4 Marginal Land Zoning and Industrial Discounts

In the main text, we estimate the industrial land discount based on all incremental land supply in a given year. One concern is that, the government considers adjusting land use for a particular set of marginal land parcels, and it is for these marginal land parcels that we should compare industrial discount with the marginal future tax revenues. In this appendix, we identify marginal land parcels and calculate the city-level industrial discount that puts more weight on the marginal land parcels. The industrial firms' output should be largely insensitive to which land parcel to operate, conditional on those sold in the same year by the same city government.

Suppose a local government considers selling a parcel $i$ of land, in time $t$, as either residential or industrial. Let $U_{i,t}^{res}$ represent the government's difference in utility from selling the parcel as residential instead of industrial land; the government sells the parcel as residential if $U_{i,t}^{res} > 0$, and as industrial otherwise.

$$U_{i,t}^{res} = g(X_i) + \xi + \epsilon_{i,t}^{res} \tag{33}$$

In Eq. (33), $g(x_i)$ captures land $i$'s tendency to be used as residential, and $\xi$ represents the government's overall tendency to sell residential land versus industrial land. Assume $\epsilon_{i,t}^{res}$ is i.i.d. and follows Type I extreme value distribution. The probability of a parcel with characteristics $X_i$ being sold as residential is:

$$p(X_i, \xi) \equiv \frac{\exp(g(X_i) + \xi)}{1 + \exp(g(X_i) + \xi)} \tag{34}$$

Let $f(X)$ be the density function over land parcel characteristics. Given $\xi$, the expected total industrial land discount the total industrial land supply are:

$$\begin{aligned} ID(\xi) &= \int_X f(X) \cdot Area(X) \cdot (1 - p(X, \xi)) \cdot IndDisc(X) \cdot dX \\ IS(\xi) &= \int_X f(X) \cdot Area(X) \cdot (1 - p(X, \xi)) \cdot dX \end{aligned}$$

By shifting $\xi$, the local government can adjust the aggregate land allocation between residential and industrial uses. Imagine now the local government decreases $\xi$ to increase industrial land supply, the cost that it will incur in the form of industrial land discount per square meter of land is

$$\frac{ID'(\xi)}{IS'(\xi)} = \frac{\int_X f(X) \cdot Area(X) \cdot p'(X, \xi) \cdot IndDisc(X) \cdot dX}{\int_X f(X) \cdot Area(X) \cdot p'(X, \xi) \cdot dX}$$

Now, by differentiating (34) and rearranging, we can find that:

$$\frac{\partial p(X, \xi)}{\partial \xi} = p(X, \xi)(1 - p(X, \xi)) \tag{35}$$

Hence, the marginal industrial land discount per square meter of land is essentially the average $IndDisc$ weighted by:

$$Area(X) \cdot p(X, \xi)(1 - p(X, \xi)) \tag{36}$$

Expression (36) states that the marginal industrial land discount loads more on land parcels with higher $p(X, \xi)(1 - p(X, \xi))$. Intuitively, this term is $\frac{\partial p(X,\xi)}{\partial \xi}$, which captures how much small changes in the government's preference to sell residential land changes the *likelihood* of a given parcel $i$ being sold as residential. The adjustment term is maximized when $p(X, \xi) = 0.5$, and is smaller when the probability of residential sales is very large or very small. This framework captures the intuition that parcels which have an intermediate likelihood of being sold as residential land are most "marginal". In contrast, when $p(X, \xi)$ is very close to 1 or 0, the government has a strong preference to sell the parcel as industrial or residential; small changes in $\xi$ will not change the likelihood of selling the parcel as industrial versus residential substantially.

Table A.2: Estimating Industrial Discount With Marginal Land Zoning

Panel A: Model Predicted Residential Land Zoning

| Model | Observed Land Zoning | |
|---|---|---|
| | industrial | residential |
| Logit | 0.34 | 0.82 |
| | 0.23 | 0.24 |
| | 467,486 | 871,144 |
| | | |
| Nearest neighbor | 0.24 | 0.87 |
| | 0.29 | 0.23 |
| | 470,920 | 874,175 |

Panel B: National Average Industrial Land Discount

| Model | IndDisc |
|---|---|
| Simple Average | 1794.19 |
| Logit | 1810.40 |
| Nearest neighbor | 1793.98 |

Note: Panel A shows the predicted probability of land zoning as residential versus industrial for the industrial and residential land separately, based on the local Logit model or the nearest neighbor model. Each cell reports the mean, standard deviation and number of observations. Panel B shows the national average of the city-level industrial land discounts during 2007-2010, using simple average and weighted by zoning probability predicted by local Logit model and the nearest neighbor model.

**Implementation.** To implement the estimation, we adopt two approaches to the estimation of $p(X, \xi)$. The first approach is to assume a linear Logit model, i.e., $g(X_i) = X_i\beta$, where $X_i$ includes the second-order polynomial of log land area and distance to the urban center. As the geographic pattern of land use should be consistent over time, we pool 2007-2019 together and estimate $(\beta, \xi)$ for each urban unit separately.

The second approach is the nearest neighbor. This approach makes use of the fact that land parcels with the same use tend to cluster together. For each land parcel $i$ in the urban unit $u$, we select all the land parcels within a distance of $k_u$ and calculate the share of these neighbors being residential, $p_i(k_u)$, as an estimate of the probability of residential zoning for $i$. Then for all the land parcels in the urban unit $u$ during 2007-2019, we choose $k_u$ to maximize the log likelihood of the observed outcome:

$$k_u^\star = \arg\max_{k_u} \mathcal{L}(k_u) = \sum_i \log\left(\mathbf{1}_i^{res} p_i(k_u) + \mathbf{1}_{i,t}^{ind}(1 - p_i(k_u))\right)$$

The estimated probability of zoning as residential is then $\hat{p}_i = p_i(k_u^\star)$.

The results are shown in Table A.2. Panel A shows the performance of the two models in predicting land uses. Both models do reasonably in predicting the land use, while the nearest

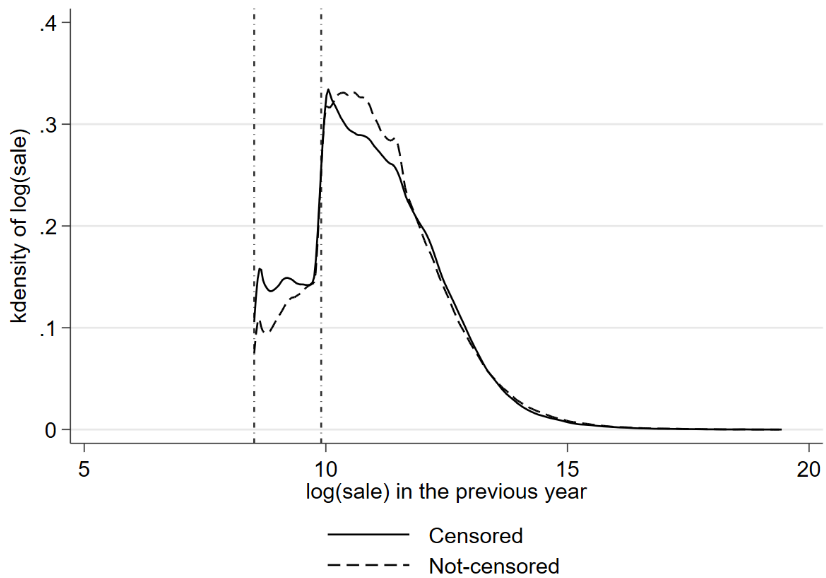



Figure A.4: Distribution of Log(Sale) in the Previous Year

Note: This figure reports the kernel densities of the past year log(sale) for firms that do and do not exit in a given year separately. For 2011, the past year is 2009 as we do not have data for 2010. The two vertical dashed lines represent the censoring boundaries, which is 5 million RMB before 2011 and 20 million RMB after 2011.

neighbor model performs slightly better than the Logit model. Panel B shows national average industrial discounts in the baseline specification, as well as using the re-weightings from the Logit model and the nearest neighbor model. We find that the estimates of industrial discounts barely change with the re-weightings.

### B.5 Firm Panel Imbalance

In this subsection we analyze the causes and consequences of panel imbalance in our difference-in-differences design. As noted in Section 2.2, firms enter and exit our panel due to data linkage issues, firm births and deaths, and sales falling below a threshold for inclusion in our data. While panel imbalance arising from data linkage issues is likely to be idiosyncratic, there is a concern that left-censoring due to sales falling below the threshold for inclusion could affect our estimate of the effect of land purchase. To assess the importance of censoring, we test whether panel imbalance (firm attrition) is more likely for firms close to the censoring boundary: to the extent that panel imbalance is idiosyncratic, we should not see differences in the distribution of sales for firms that do and do not attrite.

Figure A.4 shows the results of this test in the form of kernel densities of past-year sales, separately for firms that do and do not attrite in a given year. We see the two distributions are strikingly similar. If anything, firms near the 2011 censoring boundary (denoted by the second of

Table A.3: Survival Rates of the Matched Sample

| Event Year | 2007 | | 2008 | | 2009 | | 2010 | |
|---|---|---|---|---|---|---|---|---|
| Treat | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |
| t=-4 | 37% | 39% | 59% | 57% | 64% | 57% | 56% | 49% |
| t=-3 | 81% | 78% | 78% | 73% | 79% | 75% | 68% | 64% |
| t=-2 | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |
| t=-1 | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |
| t=0 | 87% | 100% | 75% | 100% | 84% | 100% | | |
| t=1 | 68% | 87% | 59% | 78% | | | 63% | 100% |
| t=2 | 55% | 71% | | | 50% | 71% | 59% | 95% |
| t=3 | | | 36% | 52% | 46% | 68% | 54% | 89% |
| t=4 | 32% | 48% | 32% | 46% | 40% | 63% | | |
| t=5 | 29% | 44% | 29% | 42% | | | | |
| t=6 | 26% | 41% | | | | | | |

Note: This table reports the survival rates, i.e., the percentage of firms remaining in the sample in each year, for the treated and matched control firms for each event year. Note the rates are 100% for the two years with data before the event year by construction.

the two vertical dashed lines in the figure) are dispropotionately likely to be *not* censored. We are reassured that the role of censoring is likely modest in generating panel imbalance.

We also examine whether panel imbalance varies by treatment status (land purchase). Table A.3 shows the survival rates of the treated and matched control firms for each event year, i.e., the percentage of firms remaining in the sample. By construction, all the firms are observed in the two years before treatment. There is not much difference between the treated and control firms in $t = \tau - 3$ and $t = \tau - 4$ in terms of the survival rates, confirming that the matching generates a comparable control group for the treatment group. However, after the treatment year, the survival rate of the treatment group is higher than that of the control group. This is consistent with the firm's expansion on the newly acquired land increasing sales and making the firm more likely to stay above the censoring threshold. While our evidence in Figure A.4 suggests the consequences of such censoring is likely to be modest, this does imply that our estimate of the treatment effect of land purchase is conservative: when the control firms exit the sample, dropping this observation removes a higher difference between the treated and control firms in sales, so dropping out these pairs will make the treatment effect estimates downward biased. This ultimately translates into a corresponding downward bias in our estimates of the effects of land sales on tax revenues, and hence a downward bias in our estimate of local governments' IDR from land sales.

### B.6 Estimating Marginal Effect of Land Purchase on Sales

Table A.4 reports the estimates of specification (14) for each purchase year $\tau \in \{2007, 2008, 2009, 2010\}$ separately.

Table A.4: Dynamic Treatment Effect of Land Purchase on Sales

| Event Year | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|
| Dep Var: sale change | (1) | (2) | (3) | (4) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau-4}$ | 2.926 | -17.28 | -16.84 | 78.55 |
| | (0.0200) | (-0.205) | (-0.229) | (0.491) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau-3}$ | -30.64 | -35.27 | -66.02 | 236.8* |
| | (-0.417) | (-0.436) | (-1.086) | (1.813) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau-2}$ | -56.99* | -6.641 | -48.77 | 96.40 |
| | (-1.669) | (-0.114) | (-1.056) | (1.603) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau}$ | 170.8*** | 226.3** | 124.5** | |
| | (2.765) | (2.185) | (2.185) | |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+1}$ | 213.7** | 355.5** | | 730.0*** |
| | (2.001) | (2.027) | | (4.320) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+2}$ | 313.9* | | 578.4*** | 1,007*** |
| | (1.879) | | (3.137) | (3.215) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+3}$ | | 2,093*** | 658.2*** | 1,343*** |
| | | (3.550) | (2.659) | (3.222) |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+4}$ | 994.1** | 1,786*** | 430.3 | |
| | (2.395) | (2.590) | (1.326) | |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+5}$ | 928.9 | 2,641** | | |
| | (1.607) | (2.259) | | |
| $\overline{\Delta/S} \cdot \mathtt{Treat} \cdot \mathbf{1}_{t=\tau+6}$ | 1,505** | | | |
| | (2.190) | | | |
| Firm FE | Yes | Yes | Yes | Yes |
| Province-Industry-Year FE | Yes | Yes | Yes | Yes |
| Observations | 9,236 | 4,088 | 13,003 | 16,681 |
| R-squared | 0.673 | 0.673 | 0.657 | 0.660 |

Note: This table reports estimation results of Model (14) with the matched sample. We drop matched pairs whenever the treated or the control firm exits the sample. For each treatment year $\tau \in \{2007, 2008, ..., 2010\}$, the sample ranges from $\tau - 4$ to 2013. (Since 2010 data are missing, we do not have estimators for year at $t = 2010$.) The variable sales is in 1,000 RMB and $\bar{\Delta}$ is in 1,000 $m^2$. The year of $t = \tau - 1$ is used as the base year. Standard errors are clustered by firms. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## B.7 Estimating Marginal Industrial Tax Rates

In this section, we explain how we estimate marginal industrial tax rates.

The main tax paid by industrial firms is the value-added tax (VAT). The VAT is based on the value added by the firm during each production stage. In practice, it is calculated using the firm's output times the VAT rate minus all the input times the VAT rate, which corresponds to the accumulative VAT paid by all upstream firms. As a result, the accumulative VAT paid until firm $i$ equals firm $i$'s output value times the VAT rate. The VAT rate may differ across firms in different industries, and foreign exports are taxed at a lower rate than domestic sales. In the data, we observe the firm's output times VAT rate (Xiaoxiangshuie in Chinese), and hence we can regress it on the firm's output value to calculate the average VAT rate.

To show that this method produces reasonable results, in Figure A.5, we show a scatterplot and a binned scatterplot of firms' accumulated tax against firms' output. The scatterplot shows that the ratio of accumulated tax to output differs nontrivially across firms: some firms pay a smaller share of output as accumulated tax than others. However, the binscatter shows that the relationship between accumulated tax and output across firms is well described by a straight line passing through 0, with slope 12.10%. This means that, on average, firms pay roughly 12.10% of output as taxes, and this does not vary substantially across firms of different sizes.

Besides value-added taxes, firms also pay income taxes and a variety of administrative fees, which we will collectively call $ITF_{j,t}$. Income taxes and fees are charged based on the firm's profit; we will assume these are homogeneous across industries. If we ignore wages and predict the firm's profit with value-added ($S_{j,t} - COGS_{j,t}$), we can write:

$$ITF_{j,t} = (S_{j,t} - COGS_{j,t}) \cdot \psi_t$$

Following a similar logic to our calculations for value-added taxes, the accumulated income taxes and fees associated with firm j's output, paid by j and its upstream suppliers, is $S_{j,t} \cdot \psi_t$. Since we do not observe accumulated income taxes and fees in the firm data, we instead estimate the rate $\psi_t$ by regressing income taxes and fees, $ITF_{j,t}$, on firms' value-added, $S_{j,t} - COGS_{j,t}$. The estimate for the marginal rate is 5.77%, with a tight 95% confidence interval of [5.72%,5.83%].

In the end, our estimate of the firm tax rate is $(12.10\% + 5.77\%) = 17.87\%$

### B.8 Complementary Evidence of Land Tax Yields

Figure A.6 plots the average VAT per square meter of industrial land by province (Panel (a)) and the minimum tax requirement by industry (Panel (b)).

### B.9 Estimating Marginal Residential Tax Rates

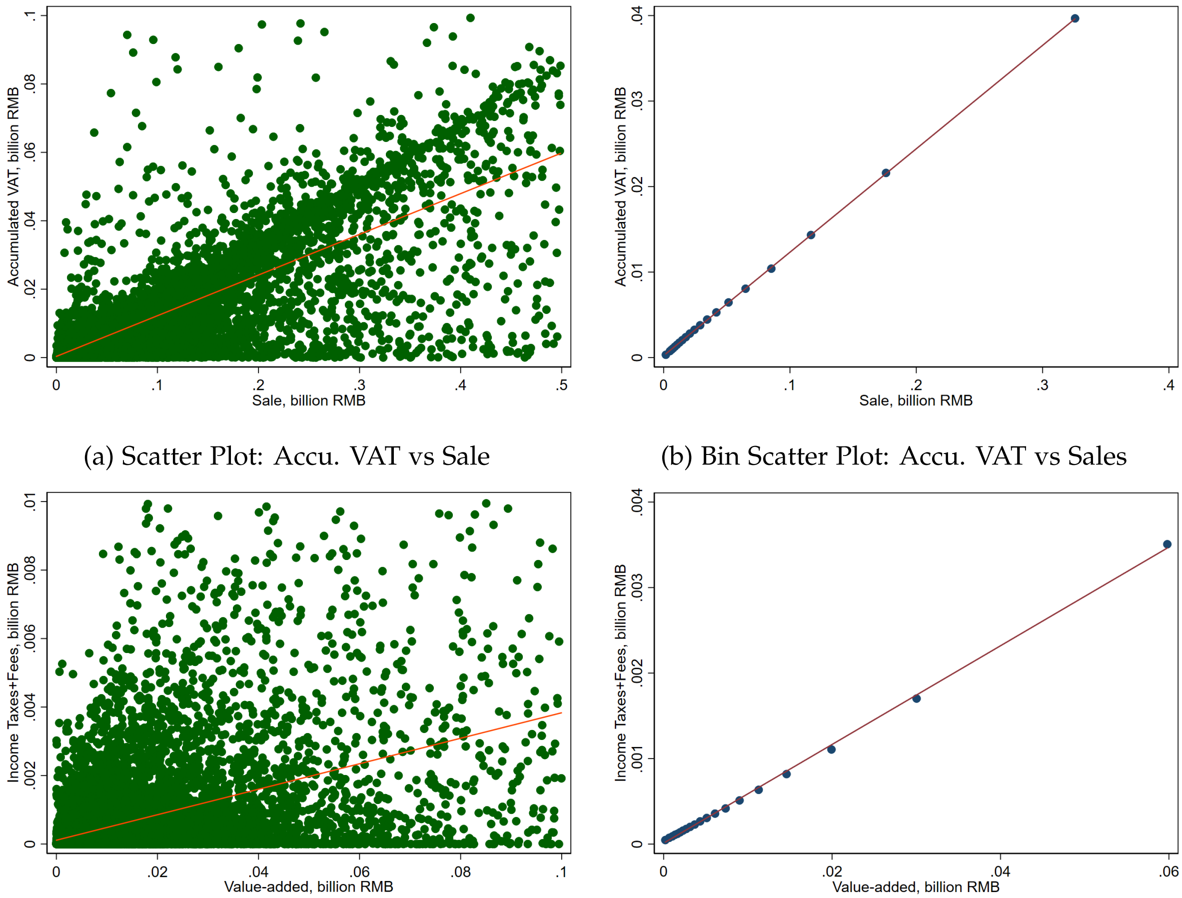
Figure A.7 shows a scatter plot and binned scatter plot of the listed home developers' annual taxes and sales during 2007-2015.

### B.10 Classification of Targeted Industries

Table A.5 shows the list of industries that were ever targeted by one or both of the Five-year Plans initiated in 2006 and 2011.

### B.11 Firms' Cost of Capital

We use listed firms that are classified to be in the industrial sector by WIND from 2007-2024 to calculate firms' cost of capital. We first estimate their costs of equity with the capital asset pricing




(a) Scatter Plot: Accu. VAT vs Sale

(b) Bin Scatter Plot: Accu. VAT vs Sales

(c) Scatter Plot: Income Tax + Fees vs VA.

(d) Bin Scatter Plot: Income Tax + Fees vs VA.

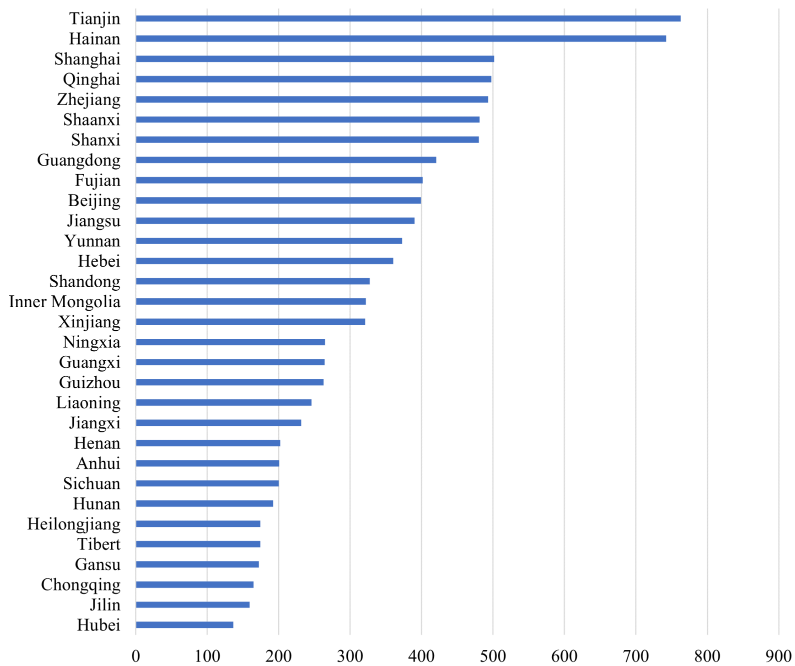
Figure A.5: Marginal VAT Rate and Income Tax and Fees Rate

Note: Panel (a) is the scatter of the "accumulated VAT" vs. sales based on a randomly chosen 1% of the sample and Panel (b) is the bin scatter of the two based on the full sample. Panel (c) is the scatter of corporate income tax plus fees vs. value-added (i.e., output minus input) based on a randomly chosen 1% of the sample and Panel (d) is the bin scatter of the two variables based on the full sample.

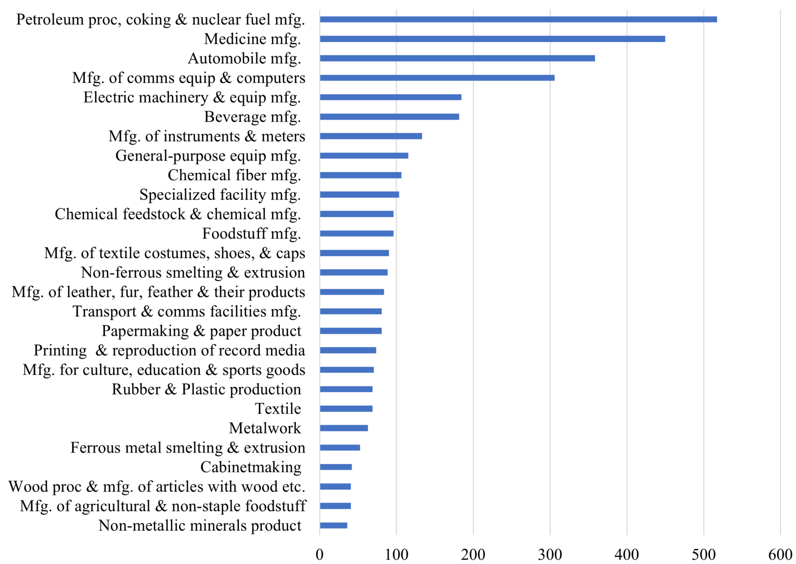
model (CAPM) as follows:

$$R_{j,e} = R_f + \beta_j \times (R_m - R_f),$$

where $R_{j,e}$ is the cost of equity of firm j, $R_f$ is the risk-free rates, $\beta_j$ is the market risk coefficient, and $R_m - R_f$ is the market return premium. We measure $R_f$ with the return rate of the 10-year bonds issued by China Development Bank, a more liquid benchmark for risk-free rates. We calculate $\beta_j$ using the weekly stock return during the past year. For market equity premium, we use the estimates developed by Damodaran (2025), who calculate the equity premium in developing countries using the equity risk premium in developed markets (i.e., the US) plus national risk premium that are indicated by Moody's rating-based default spread.




(a) Total VAT Over Industrial Land for Each Province, 2011, RMB/$m^2$



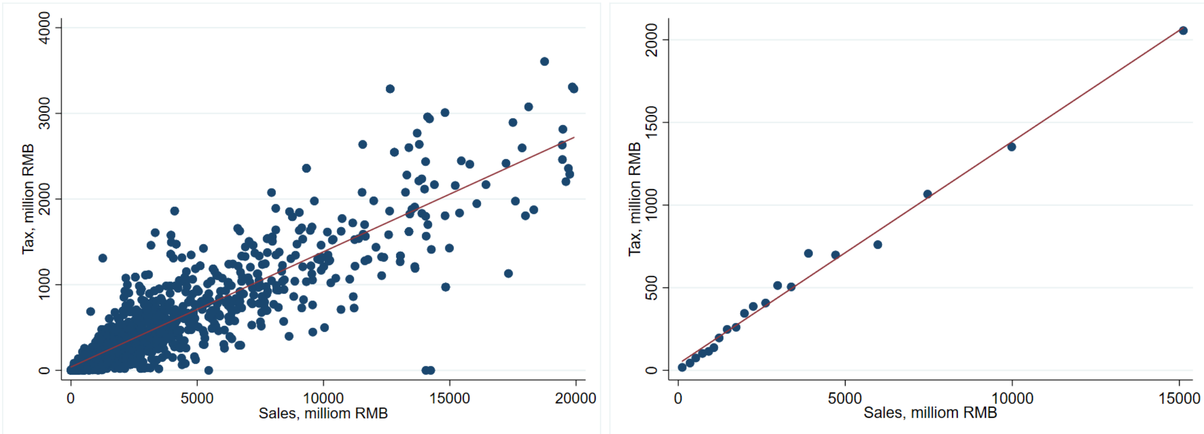

(b) Minimum Tax Requirement on Industrial Land, RMB/$m^2$

Figure A.6: Supplementary Evidence on Land Tax Payment

Notes: Panel (a) plots the average VAT per square meter of industrial land across provinces in 2011. Panel (b) plots the industry-specific requirement on minimum firm tax payment on industrial land set by Jiangsu Province in 2018 and Hunan Province in 2020. Values are in RMB/$m^2$.

We then measure the firm's cost of capital as:

$$R_{j,A} = R_{j,e} \cdot \frac{E_j}{E_j + D_j} + R_{j,d} \cdot \frac{D_j}{E_j + D_j},$$




(a) Scatter Plot: Developer Tax vs Sales (b) Bin Scatter Plot: Developer Tax vs Sales

Figure A.7: Marginal Total Tax Rate of Home Developers

Note: Panel (a) is the scatter plot of the listed home developers' total annual taxes against their sales during 2008-2020 and Panel (b) is the bin scatter.

Table A.5: Targeted Industries of Five-Year Plan 2006 & 2011

| Targeted Industries |
|---|
| Mfg. of agricultural and non-staple foodstuff |
| Chemical feedstock and chemical mfg. |
| Medicine mfg. |
| Non-ferrous smelting and extrusion |
| Specialized facility mfg. |
| Transport and comms facilities mfg. |
| Automobile mfg. |
| Electric machinery and equip mfg. |
| Mfg. of comms equip, computers and other electronic equip |
| Production and supply of electric power and heat power |
| Gas generation and supply |
| General-purpose equip mfg. |
| Exploitation of petroleum and natural gas |
| Chemical fiber mfg. |
| Coal mining and washing |
| Ferrous metal smelting and extrusion |

Note: This table lists the industries that were ever targeted by one or both of the two Five-year Plans initiated in 2006 and 2011, which cover the period 2006-2015.

where $R_{j,d}$ is the cost of debt, $E_j$ is the market value of equity and $D_j$ is value of debt at the beginning of the year. We measure $R_{j,d}$ with the interest payment divided by the average

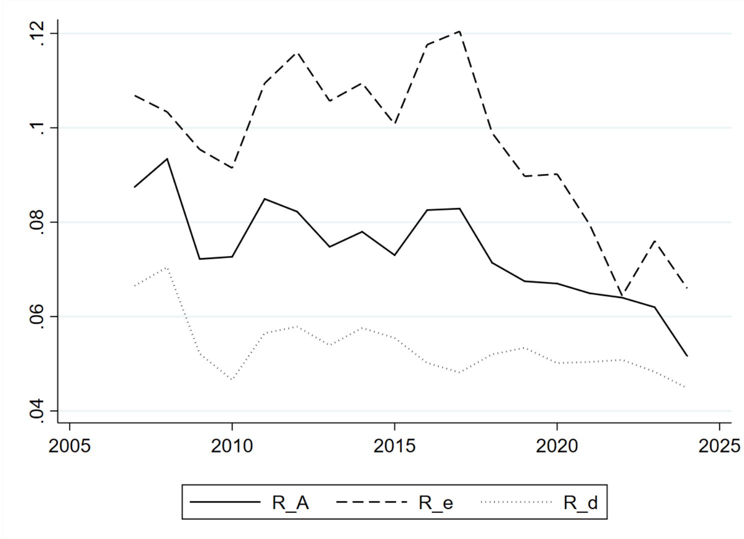



Figure A.8: Cost of Capital ($R_A$) of Listed Firms in the Industrial Sector

Note: This figure plots the cost of capital, i.e., the value weighted average of cost of equity and cost of debt, for the publicly listed firms that are classified in the industrial sector.

interest-bearing debt at the beginning and the end of the year.

Figure A.8 reports the average $(R_{j,A}, R_{j,e}, R_{j,d})$ over time.

# C Supplementary Materials for Section 5

## C.1 Guangdong Policy Changes in 2016

The main policy change that most provinces made in 2016 was to change the share of VAT taxes accruing to city governments. However, Guangdong is an outlier: it did not change the city government VAT tax share, but implemented a number of other policies to encourage city governments to allocate more industrial land. These policies thus confound our analysis of the effect of VAT tax changes on industrial land sales. When we include cities in Guangdong when estimating Equation (26), there are no significant results from dynamic treatment effect analysis (the results are available upon request).

Guangdong made the following policy changes in 2016. All cities within the province were required to specify a region within which all land had to be sold as industrial, not residential land. Cities were also broadly required to guarantee "sufficient" industrial land supply to advanced manufacturing industries. Incentives to do so included, for example, policies stating that industrial land allocated to major investment projects would not count towards land quotas, that is, the maximal amount of land that cities could sell within a certain period of time.

These policies were imposed upon city governments and supervised by the provincial govern-

Table A.6: Industrial Land Supply and Reward in Guangdong

| Dep Var: Reward | (1) | (2) | (3) |
|---|---|---|---|
| Share of industrial land supply | 0.380* | 1.963* | 1.215* |
| | (1.689) | (1.843) | (1.931) |
| Observations | 121 | 118 | 118 |
| $R^2$ | 0.138 | 0.0776 | 0.0788 |
| Spec | OLS | Logit | Probit |
| City FE | Yes | Yes | Yes |

Note: This table reports the correlation between the share of industrial land supply in 2017 and whether the district/county received reward in 2019 across the 118 districts/counties in Guangdong. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

ment. Cities which experienced higher growth in manufacturing were to be rewarded with larger quotas for future land sales. To verify in the data that this policy encouraged more industrial land sales, we regress an indicator for whether a city received a reward of higher land quotas in 2019, on the share of land sold as industrial in the year 2017. The results are shown in Table A.6: as predicted, cities allocating more industrial land were substantially more likely to be rewarded.

The majority of these policies were applied only in the Guangdong province.[25] These policies are likely to have contributed to Guangdong increasing industrial land supply, despite the fact that the city government VAT share in Guangdong stayed constant in 2016. Thus, we drop Guangdong from our event study analysis.

[25] Two exceptions are that the policy of rewarding cities with higher manufacturing growth with larger land quotas was also implemented in Guangxi in 2017, and Sichuan in 2019.