Zoning for Profits: How Public Finance Shapes Land Supply in China[*]

Zhiguo He, Scott Nelson, Yang Su, Anthony L. Zhang, Fudong Zhang

December 2023

Abstract

Public finance and real estate are intertwined in China, where local governments are monopolistic land suppliers. We study how tax benefits associated with land zoning, in addition to the direct land sale prices, are essential for understanding local governments' land allocation decisions. First, we show that the large (10-fold) price premium for residential-zoned relative to industrial-zoned land can be explained by their future tax difference: industrial- and residential-zoned land generate similar long-run pecuniary benefits once their tax benefits are taken into account. Second, we find suggestive evidence that tax incentives do shape local governments' land zoning: industrial land supply increases with local governments' industrial tax share and decreases with their cost of capital.

Keywords: Municipal Finance, Land Zoning, Municipal Corporate Bonds, Tax Sharing, Housing Markets

JEL classifications: H70, G31, R14, R38

[*]He: Stanford University and NBER, hezhg@stanford.edu; Nelson: University of Chicago Booth School of Business, Scott.Nelson@chicagobooth.edu; Yang: Chinese University of Hong Kong Business School, yangsu@cuhk.edu.hk; A. Zhang: University of Chicago Booth School of Business, anthony.zhang@chicagobooth.edu; and F. Zhang: Tsinghua University PBC School of Finance, zhangfd@pbcsf.tsinghua.edu.cn. The paper was previously circulated with the title "Industrial land discount in China: A Public Finance Perspective." This paper was completed while Zhiguo He worked at University of Chicago and acknowledged financial support from the John E. Jeuck Endowment at the University of Chicago Booth School of Business. This research was funded in part by the Tsinghua University – University of Chicago Joint Research Center for Economics and Finance. Yiren Ding, Xuechen Hong, Willy Yu-Shiou Lin, and especially Futing Chen provided outstanding research assistance. We are grateful to Ting Chen, Ernest Liu, Chad Syverson, Jing Wu, and Qinghua Zhang for comments, and Wei Jiang, Xiao Cen, Zhuo Chen, and Li-an Zhou for sharing data.

1 Introduction

China's real estate sector is intertwined with municipal finances in an important way: Chinese city governments derive a large fraction of their revenues from both direct land sales and associated future tax revenues. Understanding the interactions between land markets and local public finance, which is often referred to as "land financing" (e.g., Lin and Yi, 2011), is thus important for understanding China's land markets and the country's industry structure (i.e., real estate versus manufacturing) more broadly.

City governments in China have large discretion over zoning of newly sold land parcels; most land parcels are zoned as either residential or industrial. The zoning choice has important fiscal consequences: during 2007–2019, residential land sold for around 10 times more than industrial land. A common view in the literature is that Chinese local governments sell residential land primarily to raise revenue, whereas industrial land is sold primarily for nonpecuniary reasons, such as to subsidize industry or support labor demand. In support of this view, Liu and Xiong (2020, pp. 193) state that "it is a common practice for local governments throughout China to offer industrial land at subsidized prices to support local industries."[1]

This paper proposes that there is an important flaw in this common view: due to the dual role of local governments as both land suppliers and tax recipients, the total payment that local governments receive from the land supply should be the up-front land sales plus the associated long-run tax revenues. While industrial land sales generate lower sales revenues up front, industrial firms pay taxes in the future; in contrast, residential land sales yield larger up-front sales revenues, but no long-run tax revenues. We quantify the tax flows generated by industrial land sales and show they are large enough such that the total present value of pecuniary benefits from industrial and residential land supply are actually similar, under reasonable discount rates. Moreover, we also find suggestive causal evidence that tax incentives affect local governments' land zoning decisions: when the city governments' borrowing cost increases or their share of industrial tax revenues decreases, local governments sell more residential and less industrial land. These results not only confirm the importance of tax benefits for understanding land allocation in China, but also imply that shocks to local government finances have potential knock-on effects on land allocation and industry structure.

[1] There is a broad narrative that holds China "favor[s] industry and investment over the service sector and domestic consumption"; and in more recent years, China has shifted to target subsidies at specific "strategic" industrial sectors (Liu, 2019). The analysis of the choice between residential and industrial land sales is more in line with the first broad-based industrial policy, rather than the second policy of subsidies targeted at specific sectors.

To develop these results, we begin with some key institutional details. Land sales account for a substantial fraction of Chinese local governments' revenues.[2] The central government imposes caps on the total amount of land that can be sold within a city, but city governments have large discretion on how to zone the land. Land use rights are sold to industrial firms to build factories and warehouses or home developers to build apartments and houses; the sales revenue from land accrues directly to local governments. Besides direct land sale revenues, each type of land use leads to a different stream of future tax revenues. For residential land, governments can collect one-time tax revenues from home developers, but no further tax revenues given the lack of residential property taxes in China. For industrial land, local governments collect continuing tax revenues from industrial firms. Tax revenues are shared among various levels of governments.

Therefore, the total "price" paid by buyers to sellers includes not only the up-front land price but also future tax payments. To combine land sale revenues with tax revenues and evaluate whether governments collect more from residential land than industrial land, we measure the *Internal Rate of Return* (IRR) on industrial land sales. We can think of the decision to sell industrial land as akin to a firm's investment problem, where the upfront cost is the "industrial discount"—the gap between industrial and residential land prices—and the future payoffs are the higher taxes from industrial land relative to residential land. This analogy suggests the use of IRR, which is the discount rate that equates the net present value of cash flows between industrial and residential land, as a measure of the relative return to sell land as industrial rather than as residential.

We note that IRR calculations do not rely on local government objectives or land market conditions. Instead, IRR serves as a convenient tool to assess the significance of tax revenues compared to land sale revenues. There are two ways to interpret the IRR. First, it is an assessment of the return from the industrial land parcel based on cash flows directly associated with the land itself. Because the IRR does not factor in price impacts, comparing IRR to the government's discount rate does not directly tell us whether the government can profit more or less when changing the land use of one parcel on the margin. Second, assuming competitive land demand, the total payment from marginal land buyers (land sale plus tax revenues) should match the pretax benefits of additional land supply to the private sector. Then, the comparison between IRR and the government's discount rate informs us about land allocation efficiency: a lower IRR suggests an oversupply of industrial land and an undersupply of residential land; a higher IRR implies the opposite.

[2] In 2019, local governments' fiscal revenue primarily came from three sources: 10 trillion RMB from general revenue, 7.5 trillion RMB from central government transfers, and 7.3 trillion RMB from land sales.

When would the IRR on industrial land sales equal the government discount rate? To answer this question, we consider a model of land allocation under general assumptions about governments' objectives and market conditions. We first show that in the benchmark scenario where the local governments (1) internalize all the tax revenues, (2) are not myopic, (3) do not care about nonpecuniary benefits, and (4) do not have market power in the land markets, the equilibrium IRR equals the government discount rate. We then show that while some deviations from the benchmark scenario would lead to more industrial land supply (e.g., governments' concern for nonpecuniary benefits, market power in the residential land market), other deviations (e.g., intergovernmental tax sharing, local official myopia) would lead to the opposite. Therefore, it is unclear how the equilibrium IRR would compare to the governments' discount rate.

We move on to measuring the IRR on industrial land, which requires estimating three quantities: the average discount on industrial land versus residential land; the long-term increase in tax revenues from firms that purchase industrial land; and the one-time tax revenues paid due to home development. We emphasize that all inputs are based on their respective sample periods and do not suffer from the usual "look-ahead" bias.

We measure these quantities using three datasets. The first contains data on the universe of land parcels sold by the government from 2007 to 2019. We observe the price of each parcel, the land zoning, the buyer name, and characteristics of the parcel such as location and size. The second contains data on large Chinese industrial firms during 1998–2013. The last is annual financial reports from listed developers during 2008–2021. By merging the first two datasets, we are able to identify the industrial firms that acquired each land parcel during 2007–2010, for which we can estimate the consequent effect on firm taxes for at least four years. Our primary estimates of the IRR on industrial land are hence based on land sales during 2007–2010.

We estimate the industrial discount based on a potential-outcomes framework. We use observed residential (industrial) sale prices to estimate a hedonic model to predict the prices of industrial (residential) land parcels if they were, counterfactually, sold as residential (industrial). The industrial discount is then calculated as the difference between the actual (predicted) residential and the predicted (actual) industrial price. During 2007–2010, we estimate the average industrial land discount to be 1012.83 RMB/m^2.

To estimate marginal tax revenues from industrial land sales, 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 2007–2010 and using firm sales and tax data until 2013, the average annual marginal taxes are 113.6 RMB/m^2 in the first three years, and 214.2 RMB/m^2 thereafter. We also estimate incremental tax revenues paid from home development and home sales, taking into account the spillover effect on upstream suppliers, which is about 2367.01 RMB/m^2 for land sales during 2007–2010.

These estimates allow us to come to the IRR on industrial relative to residential land sales. We find that during 2007–2010, the industrial land IRR is 5.80%. The estimated IRR is comparable to the usual range of local governments' cost of capital, which when proxied by their bond yields, ranges between 3.5% and 7.5% with an average value of 5.0%. The conclusion is robust to various robustness checks that address potential biases to the IRR estimates (e.g., government subsidies, alternative timing of cash flows). Thus, contrary to the common view that only considers land prices, industrial and residential land generates similar long-run payment once the associated tax benefits are taken into account. This result highlights the importance of associated tax benefits in understanding land allocation in China. We clarify that this result does not imply that governments can always make efficient land allocation decisions. It is more likely an incidental outcome driven by various government objectives and market conditions as we discuss above.

In fact, the IRR of industrial land is likely to have gone below the government discount rate since 2010. We take our methodology to further estimate the industrial IRR over time, with more recent industrial land discounts and home development and sales tax data but the industrial taxes held constant due to data limitations. Our estimation shows that the industrial IRR has decreased after 2010, declining dramatically since 2016 in particular. In 2019, the industrial IRR was roughly 3.03%, at the lower end of usual government discount rates. We find that this decrease over time is potentially due to the increasing share of industrial tax revenues that accrue to local governments, especially following the 2016 tax reform that doubled the local governments' share of value-added taxes.

Given the importance of tax benefits as part of land buyers' payments to local governments, finally we provide some suggestive causal evidence that tax incentives do seem to affect government land allocation decisions. We draw this conclusion based on two predictions closely related 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 capture more tax revenues from industrial land, they will sell more industrial land, increasing industrial discounts.

We test and find support for both predictions. First, supporting our hypothesis about local governments' cost of capital, we show that industrial land discounts are negatively associated with local governments' cost of capital, as measured by local governments' municipal corporate bond yields, in the cross section of cities. The negative correlation also holds when we instrument municipal corporate bond yields using a political economy–based instrument that builds on Chen et al. (2020). Second, supporting our hypothesis about intergovernmental tax sharing, we exploit a change 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 collected by city governments; note, identifying alternative explanations for this positive correlation is challenging.

The "land finance" system, through which the land market and public finance are closely intertwined, is a relatively unique feature in the Chinese setting. For the land market, our results highlight the importance of tax benefits as part of land buyers' payments to suppliers, which deserves more attention when studying China's land market and the real estate sector. For public finance, this system suggests that shocks to land prices can impact local fiscal health, and shocks to local governments' ability to raise financing in other sources can propagate into land markets and generate long-run impacts on local industry structure (i.e., real estate versus manufacturing).

Outside the Chinese setting, the idea that land zoning is affected by the tax incentives of local governments has been studied in a number of other settings.[3] Our result that land zoning decisions are sensitive to tax sharing may hold in many settings outside China. For example, since US city governments are largely funded by property taxes rather than local industrial taxes, they may be less than optimally supportive of industrial firm entry because they cannot capture much of these firms' tax revenues, whereas changes in revenue sharing schemes may influence these choices.

Literature review. Our paper is most related to the literature on the effect of local government financing. Many papers have analyzed how local governments' fiscal conditions and their debt-issuing capacities influence their expenditures, alternative sources of revenues, local policies, and real outcomes. Yi (2021), Posenau (2021), and Agrawal and Kim (2021) show that credit-constrained municipalities cut spending, especially infrastructure investment and public facility expenditures, leading to public service quality deterioration. Zhang (2021) shows that local governments' pension deficits can impact households' savings and investment in safe assets. Giesecke and Mateen (2022) show that local governments respond to negative fiscal shocks due to a large decline in property

[3]For example, see Altshuler and Gomez-Ibanez (2000) and Quigley and Raphael (2005) based on California, Burnes et al. (2014) based on Florida, and Cheshire and Hilber (2008) based on the UK.

values by increasing property tax rates. Adelino et al. (2017) show that changes in local governments' financing costs can influence local governments' employment, private sector employment, and income. Amornsiripanitch (2022) analyzes how the decline of monoline insurance affects local governments' financing costs, expenditures, and public sector employment. Pinardon-Touati (2021) shows the crowding out effect of local government debt on corporate credit and investment in France. LaPoint (2022) analyzes sales of property tax–delinquent properties and the consequences on neighborhood composition and housing disparities in the US. [4]

In this literature, a few papers have also examined the interaction between local public finance and land regulations, particularly the fiscal incentives associated with different land use types (Altshuler and Gomez-Ibanez, 2000; Blöchliger et al., 2017). For instance, 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. In Florida, Burnes et al. (2014) find that jurisdictions with higher sales tax rates prefer to attract large shopping malls over manufacturing firms through fiscal zoning. In the UK, Cheshire and Hilber (2008) investigate how 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 prices for office space.

Our paper also relates to the literature on the Chinese land market. Several recent papers have examined the drivers of the gaps between industrial, residential, and commercial land prices in China. For example, Zhang et al. (2022) put forth a similar viewpoint on the trade-off between up-front land revenue and future tax revenue in Chinese land market. Instead of comparing residential with industrial land, that paper compares residential with commercial land; more importantly, they focus on the relative supply without quantitatively comparing the tax difference to the up-front price gap.[5] Most other papers maintain that industrial land is subsidized for local governments' nonpecuniary incentives. Liu and Xiong (2020) argue the industrial price gap is due to local governments' incentives to subsidize local industries. Tao et al. (2010) document that Chinese local governments used subsidized industrial land in competition for investment. Lei and Gong (2014) argue local governments distort prices of industrial land for nonpecuniary reasons relating to industrial agglomeration externalities. Fan et al. (2015) similarly model

[4] A number of papers have investigated the consequences of pension underfunding in the US; see Cestau et al. (2019) for a recent survey for this literature.

[5] While residential land prices were about 10 times higher than industrial land prices from 2007 to 2019, they were similar to commercial land prices prior to 2014 and had roughly doubled by 2019.

nonpecuniary reasons for low industrial land prices. A number of papers also analyze how corruption affects Chinese land prices (Cai et al., 2013; Li, 2019; Chen and Kung, 2019). Tian et al. (2022) analyze how the design of land auctions affects the efficiency of land allocation in China. Other papers on China's land markets include Deng et al. (2020), Tan et al. (2020), and Henderson et al. (2022). While we may refute some explanations, our perspective is largely complementary to these alternative views.

2 Institutional Details and Data

2.1 Institutional Background

Unlike in countries such as the US, where land transactions occur directly between private parties, the majority of land transactions in China are intermediated by local governments. 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 associated 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 will focus on residential and industrial land, which accounted for 86% of the total land supplied in terms of area between 2007 and 2019.

The urban landscape is mostly regulated by two laws: the Land Administration Law and the Urban and Rural Planning Law. The 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 through the "Land Use Overall Plans" at all levels of governments and the "Urban Overall Plans" at the city and subordinate level.[6] In general, the first set of plans lists regulations about the scale of the cities, while the second gives more details on land zoning. In drafting these plans, upper-level governments (central and provincial) lay out planning guidelines that include caps on the scale of the cities, and lower-level governments (city and subordinate county and town) are in charge of specifying land

[6]The two plans have been combined into a single Territorial Spatial Plan since 2019. See here.

zoning at detailed areas until parcel level.[7] 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.

The recent lawsuit between the developer Lujiazui Corp. and Suzhou government perhaps illustrates best the assumption that local governments can adjust land zoning. The core of this lawsuit involves 14 land parcels, which were previously used as industrial land by the steelmaker Suzhou Steel Group but rezoned as residential land and subsequently sold to Lujiazui Corp by the Suzhou government.[8] In addition, we also assume that there exists a sizable set of parcels that could reasonably be zoned for either use case. One piece of supporting evidence is that, while residential parcels are systematically larger and closer to city centers than industrial parcels, the distributions of parcel characteristics have a large amount of overlap (Online Appendix Figure A.2).[9]

2.2 Data

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

Land sale data. Covering the universe of land sales by local governments in China from 2007 to 2019, the land sale data is from the Ministry of Natural Resources. For each land 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, tender, auction, and listing.[10] Agreements do not necessarily represent market-based transfers, while the latter three (tender, auction, and listing) do; throughout the paper, we will use "auction" to refer to these latter three allocation methods. We retrieve data on the geographical coordinates of land parcels using the Gaode maps API, a leading location based services provider in China. Figure 1 shows prices of industrial and residential land. Residential land prices exceed industrial land prices by a significant amount, and the price gap increases over time.

[7] In implementing the "Urban Overall Plans", the Ministry of Housing and Urban-Rural Development publishes guidelines on the split of land use types. For example, the 2012 Code for Classification of Urban Land Use and Planning Standards of Development Land states that residential land share should fall between 25% and 40% and the industrial land share between 15% and 30%, leaving city governments substantial discretion within these bounds.

[8] The developer claimed that the 14 parcels turned out to have severe soil pollution that was not truthfully disclosed at the time of purchase. See this news report from South China Morning Post.

[9] This suggests that characteristics do not fully pin down local governments' zoning decisions as, for most parcels, there exist parcels with similar characteristics but different zoning.

[10] We exclude an allocation mechanism called "administrative allotments" involving no payment from land receivers, which is used for infrastructure, government offices, military facilities, etc.

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 level. Panel A is based on the residential and industrial land auction transactions during 2007–2019; 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 2007–2019, 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.

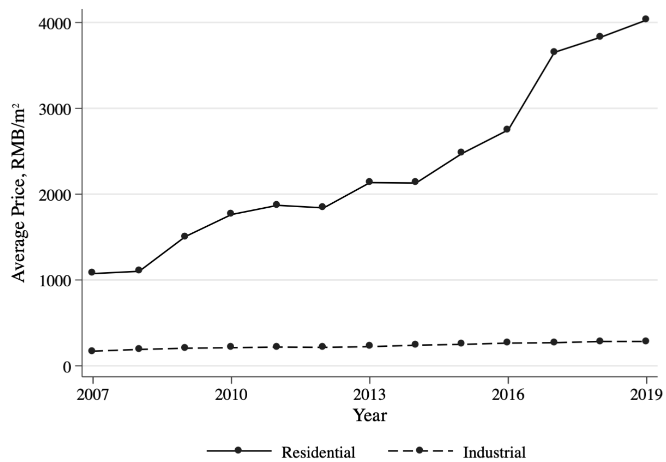


Figure 1: Average Land Prices over Time by Land Use: Industrial vs. Residential

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 2007–2019.

Firm data. To estimate the tax yield on the industrial land, we take industrial firm data from the Annual Survey of Industrial Firms (ASIF), which are collected 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 such as firm name, industry, annual sales, profits, and tax payment. Despite some concerns about the data quality (Nie et al., 2012), the data have been widely used in economic research on China.[11]

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 their subsidiaries. To simplify our estimation, we exclude firms that purchased land in multiple years during our sample. That is, in our difference-in-differences strategy, firms that purchased land (once or multiple times) in a single year during 2007–2013 form our treatment group; control firms are those that never purchased any new land during this period.

In total, we can merge 22,636 transactions out of a total 124,341 industrial land purchases by firms via agreement, tender, auction, and listing during 2007–2010. In the ASIF sample, around 3% of firm-year observations during 2003–2013 were matched to land purchases during 2007–2010. Table A.1 in the online appendix compares merged

[11]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, it is also subject to censoring and random dropout concerns, which we analyze in the Online Appendix B.6.

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 revenues collected from home developers, we use the financial information during 2007–2021 of all listed firms classified as home developers by the China Securities Regulatory Commission.

City data. We collect city-level data on GDP and population from the Urban Statistic Yearbook published by the National Bureau of Statistics. The data cover all municipal cities in China during 2007–2018.

3 Conceptual Framework

We start with the definition of the industrial land discount (Section 3.1), and then introduce the government's IRR on industrial land sales (Section 3.2). The IRR is a model-free approach to assess the return of an investment project by summarizing all future cash flows and comparing them with the up-front cost. We emphasize that the calculation of the government's IRR on industrial land sales requires no assumptions on the underlying behaviors of any agents. It is a convenient tool for us to quantify the significance of future tax revenues relative to up-front land sale revenues. We will discuss in Section 3.3 the economic meanings of the IRR guided by a stylized model with general assumptions about the governments' objectives and market conditions.

3.1 Industrial Land Discounts

We use "industrial discount" to refer to the difference in up-front sales revenues received by the government from selling industrial versus residential land. We think of the industrial discount as the up-front cost of industrial land sales as it captures the up-front forgone revenues when the government sells the land for industrial rather than residential use. Suppose a single land parcel is to be sold, and the price, if sold as industrial (residential) land, is p_t^{ind} (p_t^{res}). We define the industrial discount as:

$$\mathrm{IndDisc}_t \equiv p_t^{res} - p_t^{ind} - \lambda p_t^{res}. \tag{1}$$

Expression (1) is the gap between p_t^{res} and p_t^{ind} minus an extra adjustment term λp_t^{res}, which reflects the extra cost to the government of selling residential rather than industrial land.

There are essentially three kinds of costs that local governments incur when taking land from incumbent landowners for resale. The first is a fixed "standard" compensation amount paid to incumbent landowners to repossess land for resale; this cost applies equally to both kinds of land, so we will ignore it in computing industrial discounts. The second is a variable component of compensation to incumbent landowners, which depends on the sale price of the repurposed land: since the residential land price is higher, governments will pass on some of these higher revenues to incumbent landowners. Third, when local governments sell residential land, they often have to allocate extra land and resources for supportive functions, like education, associated with new residents. The latter two forces imply that the total costs of selling residential land are higher than the costs of industrial land. In the Online Appendix B.2, we use aggregate data on compensation to incumbent landowners and land provided for public services and estimate that the sum of these two variable costs is about 1/3 of residential sale revenues. Hence, we set $\lambda = 1/3$ in Eq. (1).

3.2 IRR on Industrial Land Sales

While industrial land generates smaller up-front sale revenues than residential land, it generates larger long-run tax revenue flows. We can thus think of governmental land zoning decisions as akin to firms' investment problems: selling a piece of industrial land is like investing in a project, where the up-front cost is the industrial discount and the payoff is the long-run tax revenues from the industrial land in excess of the revenues from the residential land. Building on this analogy, we follow the terminology in corporate finance (Berk and DeMarzo, 2017) and define the internal rate of return (IRR) on industrial land as the discount rate ρ that equates the net present value of industrial and residential land sales:

$$\mathrm{IRR}_t^{ind} \equiv \left\{ \rho : \underbrace{\sum_{s \geqslant t+1} \frac{Tax_{t,s}^{ind}}{(1+\rho)^{s-t}}}_{PV(tax^{ind})} - \underbrace{\sum_{s \geqslant t+1} \frac{Tax_{t,s}^{res}}{(1+\rho)^{s-t}}}_{PV(tax^{res})} = \underbrace{(1-\lambda)p_t^{res} - p_t^{ind}}_{\mathrm{IndDisc}} \right\} \tag{2}$$

The right-hand side of Eq. (2) is the industrial land discount, as defined in Eq. (1). On the left-hand side, $Tax_{t,s}^{ind}$ is industrial taxes per square meter of land in year s due to firms' land purchases in year t, and $Tax_{t,s}^{res}$ is residential taxes per square meter of land in year s due to home developers' land purchases in year t. Throughout, we assume that tax cash flows start to accrue one year after land purchases for both use types.

3.3 Interpretation of IRR^{ind}

There are two ways to interpret the IRR^{ind} in Eq. (2). First, it is an assessment of the return for the project per se based on its relevant cash flows. As the calculation does not take into account the resulting price impacts on other land parcels sold by the same government (Berk and DeMarzo, 2017), IRR^{ind} is not the local government's comprehensive assessment of the marginal benefit to sell the land as industrial (as opposed to residential). To the extent that firms often reallocate plants to other cities while most households do not move across cities (Harvey and Jowsey, 2019), price impacts on residential land should be much higher than on industrial land, suggesting IRR^{ind} is a lower bound for the comprehensive marginal return of selling industrial land from the governments' perspective.

Second, the comparison between IRR^{ind} and the discount rate can be seen as an indicator of land market allocative efficiency from the planner's perspective. To see this, when the land demand is competitive, on the margin the total benefit of the additional land supply to the private sector should equal the total pecuniary payment—i.e., land sales plus tax revenues—from the land buyers (and their supplier chain partners) to the local governments. If IRR^{ind} equals the discount rate, then the total pecuniary payment from the land buyers is the same for the marginal industrial and residential land, implying the same marginal benefit (to the private sector) of additional industrial and residential land supply. Note, the planner should ignore price impacts of the land allocation decision on other land sales (which are only relevant for local governments' profit maximization). Also, the only assumption underlying the above link between IRR^{ind} and land allocation efficiency (i.e., that the demand side of the Chinese land market is competitive) should largely hold in our setting;[12] it is mostly the supply side (i.e., local governments) that possesses market power in China's land market (Zhao et al., 2024).[13]

When would IRR^{ind} equal the government discount rate? In Appendix A, we model the land allocation decisions of a local government. We first consider a benchmark scenario where the local government i) internalizes all tax revenues, ii) is nonmyopic, iii) has no nonpecuniary benefits, and iv) does not possess market power. We show that

[12] As shown in Appendix A, no other assumptions, say the objectives of the local governments (e.g., whether or how much the local governments care about the nonpecuniary benefit of land supply, whether local officials are myopic) or the land demand elasticities, are required.

[13] During our sample period of 2007–2010, the Herfindahl-Hirschman index, a measure of market concentration based on the share of land purchased by different firms within a city, ranges from 1.5% to 16.0% with an average of 4.2% for residential and 0.9% to 17.6% with an average of 3.5% for industrial land across different cities.

under this benchmark in equilibrium, $\mathrm{IRR}^{\mathrm{ind}}$ equals the government discount rate.

We then show how deviations from the above benchmark would affect the equilibrium $\mathrm{IRR}^{\mathrm{ind}}$. We discuss the local governments' objective first. Local governments may internalize only part of tax revenues due to intergovernmental tax sharing. While almost all land sale revenues accrue to local governments, only about 31.66% of industrial tax revenues accrue to the city-level governments (Appendix C.1). Partial internalization of industrial tax revenues favors residential land supply and hence a higher $\mathrm{IRR}^{\mathrm{ind}}$ in equilibrium. Local officials can also be myopic, resulting in a bias towards residential land with immediate cash flows and hence a higher $\mathrm{IRR}^{\mathrm{ind}}$. Finally, local governments may enjoy certain nonpecuniary benefits associated with land supply. To the extent that nonpecuniary benefits from industrial development dominate (Liu and Xiong, 2020), this force favors industrial land and leads to a lower $\mathrm{IRR}^{\mathrm{ind}}$.

Moving on to land market conditions, here local governments often possess market power. The demand elasticity for industrial land is likely to be greater than that for residential land, as firms typically comparison shop different cities while most households do not move across cities (Harvey and Jowsey, 2019).[14] A smaller demand elasticity of residential land yields local governments a stronger market power, which can lead to rationing of residential land supply and hence decrease $\mathrm{IRR}^{\mathrm{ind}}$.

Because various deviations from the benchmark scenario often have opposite forces, it is unclear how the equilibrium $\mathrm{IRR}^{\mathrm{ind}}$ would compare to the government discount rate. As shown in Section 4, it happens that these opposite forces counteract each other and $\mathrm{IRR}^{\mathrm{ind}}$ is quite close to the government discount rates during 2007–2010.

4 Estimation

In the framework laid out in Section 3, measuring industrial land discounts and estimating $\mathrm{IRR}^{\mathrm{ind}}$ require three key quantities: (p_t^{ind}, p_t^{res}), the representative prices per square meter of industrial and residential land; $Tax_{t,s}^{ind}$, the stream of future tax revenues generated by industrial land sales at t; and $Tax_{t,s}^{res}$, the stream of taxes paid from residential project development. We estimate industrial discounts in Subsection 4.1, industrial tax revenues in Subsection 4.2, and residential tax revenues in Subsection 4.3. We combine these estimates and calculate IRRs in Subsection 4.4.

[14]One reason for household immobility is China's "hukou" residence restrictions (Li et al., 2017).

4.1 Industrial Discount Estimation

For each parcel of land indexed by i, we first estimate the price of the land if it were sold for the alternative use (industrial or residential). Let p_{it}^{res} (p_{it}^{ind}) denote the price per square meter of the land if sold as residential (industrial) land. Let $\mathbf{1}_{it}^{res}$ be a dummy representing whether parcel i is actually sold as residential. The sale price for parcel i we observe is:

$$p_{i,t} = p_{i,t}^{res} \times \mathbf{1}_{i,t}^{res} + p_{i,t}^{ind} \times (1 - \mathbf{1}_{i,t}^{res}) \tag{3}$$

Our goal is to estimate both outcomes $p_{i,t}^{res}$ and $p_{i,t}^{ind}$, only one of which is observed. The main challenge is that land parcels are not randomly zoned and it is likely that $\mathbb{E}[p_{i,t}^{res}|\mathbf{1}_{i,t}^{res} = 1] \neq \mathbb{E}[p_{i,t}^{res}|\mathbf{1}_{i,t}^{res} = 0]$ and $\mathbb{E}[p_{i,t}^{ind}|\mathbf{1}_{i,t}^{res} = 1] \neq \mathbb{E}[p_{i,t}^{ind}|\mathbf{1}_{i,t}^{res} = 0]$. For example, parcels closer to city centers are more likely to be used as residential. Therefore, one cannot simply take average observed prices of residential land parcels as predicted prices of the industrial land parcels if they were instead zoned for residential use.

We use the sample of observed residential (industrial) sale prices to estimate a hedonic model to predict the prices of industrial (residential) land parcels if they were counterfactually sold as residential (industrial). Formally, let $\mathcal{I}_{res}$ and $\mathcal{I}_{ind}$ represent the sets of parcels observed to be residential and industrial, respectively:

$$\mathcal{I}_{res} \equiv \left\{ i : \mathbf{1}_{i,t}^{res} = 1 \right\}, \mathcal{I}_{ind} \equiv \left\{ i : \mathbf{1}_{i,t}^{res} = 0 \right\}.$$

For $i \in \mathcal{I}_{res}$, we estimate the following regression specification:

$$p_{i,t} = X_{i,t} \cdot \beta^{res} + \gamma_{u,t}^{res} + \epsilon_{i,t}, \ \forall i \in \mathcal{I}_{res}. \tag{4}$$

Eq. (4) is a standard hedonic model that predicts $p_{i,t}$, the price per square meter of each residential land parcel (Wu et al., 2014; Chen et al., 2017). To control for the effects of local economic conditions (e.g., economic development, land market corruption), we construct very granular "urban units," contiguous urban clusters as identified by satellite images.[15] The average size of these urban units is only 20 square kilometers. We then match each land parcel to the closest urban unit and include urban unit–year fixed effects $\gamma_{u,t}^{res}$ to absorb any unobservable local effect. To capture price variation across land parcels within this granular urban unit, we further control for parcel characteristics $X_{i,t}$ including second-order polynomials of the log area of the land parcel, the distance to the closest

[15] We describe details of this procedure in Online Appendix B.3 and show some examples of the urban units in large and small cities in Figure A.1. These urban units are close to the towns and are much more granular than the cities or counties that are typically the level of geography unit controlled in other studies.

urban unit center, and the year-quarter in which the land is sold.

We estimate Eq. (4) 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 (4) separately for each prefecture city and separately for two time periods: 2007–2010 and 2011–2019. Since the specification (4) 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 2007–2010 (2011–2019). This leaves us with 213 (285) out of 341 cities for 2007–2010 (2011–2019), which collectively constitute 88.6% (98.4%) of all industrial and residential land sales through auction during 2007–2010 (2011–2019).

Using our estimates from the specification (4), we can then predict residential prices for industrial parcels by plugging these parcels' characteristics into Eq. (4):

$$\hat{p}_{i,t}^{res} = X_{i,t}\hat{\beta}^{res} + \hat{\gamma}_{u,t}^{res}, \ \forall i \in \mathcal{I}_{ind}. \tag{5}$$

That is, $\hat{p}_{i,t}^{res}$ is the predicted price of parcel i if it were sold as residential land. Analogously, we fit a hedonic model to industrial land parcels, with the same control variables as in (4):

$$p_{i,t} = X_{i,t}\beta^{ind} + \gamma_{u,t}^{ind} + \epsilon_{i,t}, \ \forall i \in \mathcal{I}_{ind}. \tag{6}$$

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

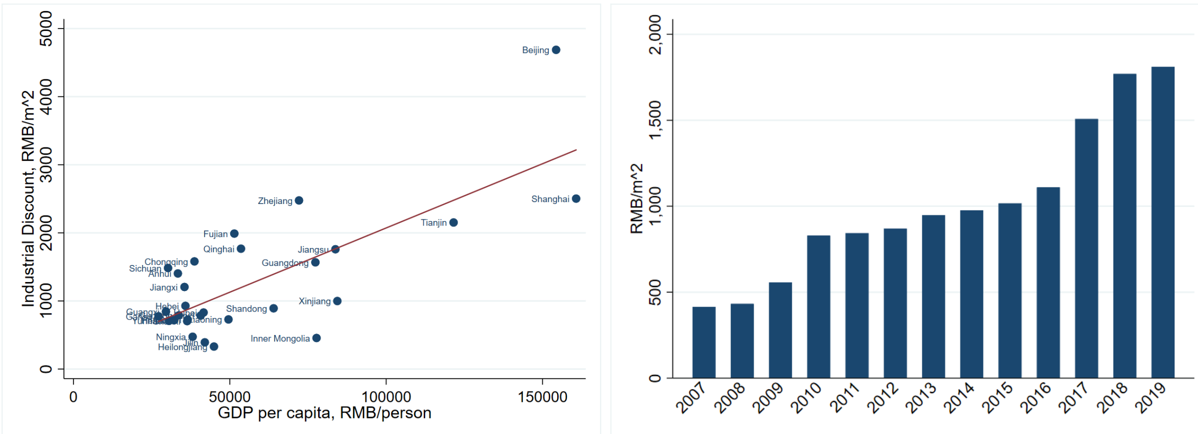
$$\hat{p}_{i,t}^{ind} = X_{i,t}\hat{\beta}^{ind} + \hat{\gamma}_{u,t}^{ind}, \ \forall i \in \mathcal{I}_{res}. \tag{7}$$

Using our estimates of $\left\{p_{i,t}^{res}, p_{i,t}^{ind}, \hat{p}_{i,t}^{res}, \hat{p}_{i,t}^{ind}, \lambda\right\}$, we can estimate industrial land discounts for each parcel using Eq. (1) as follows:

$$\mathtt{IndDisc}_{i,t} = \begin{cases} (1-\lambda)p_{i,t}^{res} - \hat{p}_{i,t}^{ind}, & i \in \mathcal{I}_{res}; \\ (1-\lambda)\hat{p}_{i,t}^{res} - p_{i,t}^{ind}, & i \in \mathcal{I}_{ind}. \end{cases}$$

The estimation delivers $\mathtt{IndDisc}_{i,t}$ at the land parcel level. We then aggregate to form city-year level estimates, $\mathtt{IndDisc}_{c,t}$, by taking averages of $\mathtt{IndDisc}_{i,t}$ weighted by each land parcel's size. Figure 2 Panel (a) shows the industrial discounts are greater in more developed provinces, and Panel (b) plots the time series of the estimated industrial discounts. It was about 400–500 RMB/m^2 during 2007–2009, increased to 750 RMB/m^2 around 2010, remained stable during 2010–2015, and increased significantly during 2016–

2019. In 2019, the average industrial discount reached about 1,800 RMB/m^2, four times the level in 2007.[16]



(a) Prov. Industrial Discount vs GDP Per Capita

(b) Industrial Discounts Over Time

Figure 2: Industrial Discount Estimates Summary.

Note: Panel (a) plots the province-level industrial land discount against the GDP per capita, both taken as simple average across cities and years (during 2007–2019) for each province. Panel (b) shows the average industrial discount estimates across cities for each year from 2007 to 2019.

Robustness checks. We comment briefly on the assumptions required for our methodology to accurately measure industrial discounts. First, to predict the counterfactual prices of the land if zoned for alternative uses, our methodology requires substantial overlap between the distributions of characteristics for industrial and residential land parcels. Appendix Figure A.2 illustrates the distributions of different characteristics for both types of parcels. Although residential land parcels tend to be larger and closer to city centers on average, the distributions have substantial overlap, enabling our counterfactual price estimates to be mostly interpolations rather than large out-of-sample extrapolations.

Second, our methodology may be confounded by unobserved differences between industrial and residential parcels, which could cause counterfactual price estimates to be biased. Importantly, the existence of such unobservable characteristics would 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 this characteristic the counterfactual residential price estimates for industrial land would be inflated. This only *strengthens* our key takeaway that future

[16]From 2007 to 2015, the simple average of residential (industrial) land price across all cities, taking predicted value if not observed, increased by a factor of 2.23 (1.41) in our data. Liu and Xiong (2020) control for changing land characteristics and show that the residential land price increased by a factor of about 3.12 while the industrial land price barely changed during the same period.

industrial tax revenues are quantitatively important relative to the up-front industrial land discount.[17]

Third, the magnitude of the bias due to unobserved factors is unlikely to be quantitatively large. Although the features of land parcels used in our pricing models, i.e., Eqs. (4) and (6), explain 50% of the variation in land prices, controlling for observable characteristics only changes average industrial discounts by around 10%. Hence, selection on observable characteristics has a relatively small effect on estimated industrial discounts. Any unobservable characteristics that can substantially affect our results would need to be both important drivers of land prices and differ greatly between industrial versus residential land parcels, as argued by Oster (2019).

Corruption is one unobserved variable known to be an important driver of land prices (Li, 2019; Chen and Kung, 2019). Our procedure does not require the absence of corruption in the land market but assumes that corruption is not different between observed and counterfactual residential and industrial land sales. For example, if half of observed residential land sales are corrupt and corruption lowers prices by 20%, our estimates remain valid if counterfactual residential land sales have similar levels of corruption and price reduction. There is no particular reason to believe the extent of corruption would be different on industrial land parcels if they were zoned as residential, since corruption is a city-level rather than parcel-level phenomenon. [18]

4.2 Industrial Tax Estimation

To estimate the effect of industrial land sales on tax revenues collected by the governments, we first employ a differences-in-differences regression to estimate the effect of industrial land purchases on firms' sales revenue, then multiply the revenue increase by the effective industrial tax rate.

[17]Controlling for land heterogeneity $X_{i,t}$ in Eqs. (4) and (6) reduces the industrial discount estimates by roughly 8%.

[18]For IRR^{ind} to be an indicator of land market allocative efficiency, the industrial discount is calculated for the *marginal* land parcels whose use is more likely to change if the government wants to adjust the annual land allocation on the margin. In Appendix Section B.5, we demonstrate an approach that can identify marginal land parcels fairly well among all land supplied in a given year and put more weight on these marginal land 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, differing by only 1.5%–2.5% quantitatively.

4.2.1 The Effect of Land Purchase on Sales

To measure the effect of purchasing one square meter of industrial land on firms' sales revenue, we compare the sales growth of land-purchasing firms to control firms matched based on similar characteristics that have not made any land purchases.

Formally, suppose that in period τ_j, firm j purchases a land parcel of size Δ_j. We assume firm j's sales in period t take the following form:

$$S_{j,t} = \begin{cases} \alpha_j + \eta_t + \varepsilon_{j,t} & t < \tau_j, \\ \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \Delta_j + \varepsilon_{j,t} & t \geqslant \tau_j. \end{cases} \tag{8}$$

Eq. (8) states that firms' sales are determined by time-varying factors η_t, time-invariant firm-specific factors α_j, and land purchases Δ_j, whose effect depends on a parameter $\theta_{t-\tau_j+1}$.

In the data, treated firms are those that have acquired some new industrial land during their presence in the sample, either through auctions or agreements. For cleaner identification, we restrict to firms that have purchased land only during one year in our sample period.[19] In contrast, control firms are those that never acquired any industrial land during the sample period (so that $\tau_j = \infty$), regardless of the transfer method.

The challenge with estimating the parameters $\theta_{t-\tau_j+1}$ in Eq. (8) is that land-purchasing firms are different from nonpurchasers, i.e., land purchase decisions may be correlated with firm-time–specific shocks $\varepsilon_{j,t}$ for $t \geqslant \tau_j$. These shocks can be decomposed as

$$\varepsilon_{j,t} = f_t(p(x_{j,\tau_j-1})) + e_{j,t}, \ t \geqslant \tau_j. \tag{9}$$

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,τ_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:

$$\mathbb{E}[e_{j,t}\mathbf{1}_{\Delta_j>0} \mid \alpha_j, \eta_t, \tau_j \in \{\tau, \infty\}] = 0, \ \forall\tau. \tag{10}$$

In words, the requirement for $e_{j,t}$ is that shocks to firm sales are uncorrelated with the decision to purchase land among firms that either purchase land in a particular year ($\tau_j = \tau$) or do not purchase land at all ($\tau_j = \infty$). The conditioning on α_j and η_t reflects

[19] If a firm purchased multiple land parcels in one year, then we aggregate these purchases together as one firm-year observation.

that the assumption only needs to hold after we control for firm and time fixed effects. Because $e_{j,t}$ is the component of firm-time–specific shocks *unrelated* to the probability of land purchase predicted by x_{j,τ_j-1}, 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 propensity scores for land purchase 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. In our data, we find these three variables are predictive of land purchase decisions. Following suggestions in 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, which are viewed as important 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 prior to τ_j. We conduct this test as part of our event study analysis below and confirm (fail to reject) parallel trends for all purchase cohorts τ.

We estimate the effects of land purchase, $\theta_{t-\tau_j+1}$, using difference-in-differences on the matched sample. To do so, we define the average land size in a given land-purchase year τ as

$$\bar{\Delta}_\tau \equiv \mathbb{E}\left[\Delta_j \mid \Delta_j > 0,\ \tau_j = \tau\right]. \tag{11}$$

Using Eq. (8), firm sales can be written as

$$S_{j,t} = \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \mathbf{1}_{\Delta_j>0} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}, \tag{12}$$

where we define

$$\varepsilon'_{i,t} \equiv \begin{cases} \varepsilon_{j,t}, & \Delta_{j,t} = 0; \\ \varepsilon_{j,t} + \theta_{t-\tau_j+1} \cdot (\Delta_{j,t} - \bar{\Delta}_{\tau_j}), & \Delta_{j,t} > 0. \end{cases} \tag{13}$$

Note that,

$$\mathbb{E}[\varepsilon'_{j,t} \cdot \mathbf{1}_{\Delta_j>0} \bar{\Delta}_{\tau_j} \mid \alpha_j, \eta_t] = 0, \tag{14}$$

where we use conditioning on α_j and η_t to reflect controlling for firm and time fixed effects. This follows from (10) thanks to the definition of $\bar{\Delta}_{\tau_j}$ in Eq. (11). In light of Eq. (14), we can consistently estimate $\theta_{t-\tau_i+1}$ with difference-in-differences estimation using regression specification (12).

Table 2: Dynamic Treatment Effect of Land Purchase on Sales

Event Year τ	2007	2008	2009	2010
Dep Var: Sales	(1)	(2)	(3)	(4)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=-4)$	192.9	-77.30	-17.82	141.4
	(0.562)	(-0.110)	(-0.0717)	(0.444)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=-3)$	2.781	185.0	-105.7	339.4
	(0.0143)	(0.337)	(-0.534)	(1.568)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=-2)$	10.21	-107.3	69.11	191.5
	(0.0936)	(-0.363)	(0.554)	(1.558)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=0)$	428.2***	938.1**	287.3**	
	(2.869)	(2.257)	(2.133)	
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=1)$	783.3***	1,097**		772.3***
	(3.235)	(2.486)		(2.695)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=2)$	687.0**		655.6**	1,048***
	(2.207)		(2.129)	(2.985)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=3)$		1,691**	602.9*	1,497***
		(2.070)	(1.678)	(3.299)
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=4)$	814.2*	2,222*	965.8**	
	(1.847)	(1.725)	(2.333)	
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=5)$	1,293*	1,600		
	(1.757)	(1.059)		
$\bar{\Delta} \cdot \text{Treat} \cdot (t-\tau=6)$	2,081**			
	(1.968)			
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Observations	9,189	4,046	13,132	16,510
R^2	0.475	0.522	0.521	0.497

Note: This table reports estimation results of Model (12) 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

Table 2 reports the estimates of specification (12). For each purchase year $\tau \in \{2007, 2008, 2009, 2010\}$, we take the year $t = \tau - 1$ to be the base year and use data from years $\tau - 4$ (there are very few firms with data before $\tau - 4$) through 2013. 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 firm tax data after the land purchase for at least three years (i.e., 2011–2013) to estimate the permanent impact of land purchase on taxes. In all regressions we also allow time fixed effects η_t to vary at the province-year level, $\eta_{p,t}$, to absorb differences in time trends across provinces.

Table 2 reveals three important patterns. First, the estimated treatment effects are positive and both economically and statistically significant. Each square meter of land generates, for example, 428.2 RMB in sales in the first year after land purchase in 2007. Second, overall, the estimated treatment effects grow over time.

Third, and importantly for validating our matched difference-in-differences 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 between the treated and control firms 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 3 summarizes the estimated treatment effects more concisely: we pool the four purchase years $\tau \in \{2007, 2008, 2009, 2010\}$ together and separately estimate a treatment effect for the first three years after purchase that captures the more modest effects on sales that we observe as firms presumably made other fixed investments (e.g., new plants) that complemented the land purchase and another treatment effect for the third and subsequent years after purchase that captures the long-run effects of new land. 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 treatment-specific time-fixed effect (Cengiz et al., 2019; Deshpande and Li, 2019). Formally, we estimate

$$S_{j,t} = \alpha_j + \eta_{t,\tau_j} + \theta_{\text{short}} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j \in \{0,1,2\}} \cdot \bar{\Delta}_{\tau_j} + \theta_{\text{long}} \cdot \mathbf{1}_{\Delta_j>0, t-\tau_j>2} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}. \tag{15}$$

In Eq. (15), the subscript τ is the event year for the treated and the matched control firms. It is stacked DID, as the time fixed effect varies with τ_j.

In the first column of Table 3 we report these estimates using land sales that occur in 2007–2010 for which we have sufficient sample to estimate long-run treatment effects; in the last four columns we report the estimated effects year-by-year. Overall, in the first three years, land purchases generate an additional 636.2 RMB/m^2 in sales on average per year; and in subsequent years land purchases generate a long-run effect of 1199 RMB/m^2

in sales on average per year.[20]

Table 3: Baseline Estimation of Marginal Output of Land

Event Year	2007-2010		2007	2008	2009	2010
Dep Var: Sales	(1)	(2)	(3)	(4)	(5)	(6)
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau \in \{0, 1, 2\})$	636.2***	577.9***	561.7**	1,003**	393.6**	751.3**
	(4.367)	(3.312)	(2.562)	(2.205)	(2.327)	(2.352)
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau > 2)$	1,199***	1,327***	1,283**	1,836*	736.3**	1,342***
	(4.453)	(3.716)	(2.050)	(1.745)	(2.073)	(2.887)
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau \in \{0, 1, 2\}) \times \text{H2}$		125.8				
		(0.553)				
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau > 2) \times \text{H2}$		-260.8				
		(-0.585)				
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE			Yes	Yes	Yes	Yes
EventYear-Province-Year FE	Yes	Yes				
Observations	43,671	43,671	9,425	4,196	13,171	16,879
R-squared	0.505	0.505	0.439	0.548	0.561	0.488

Note: This table reports estimation results of Model (15) 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 $\tau \in \{2007, 2008, ..., 2010\}$, 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

An issue commonly associated with the PS-DID method is that the identification assumption could fail if treated firms acquire new land in response to an unobserved positive shock in the same year they are impacted by the shock, despite displaying similar behavior to matched control firms prior to that year. However, we contend that this is unlikely. In reality, when impacted by an unexpected positive shock, firms will first choose on-site plant expansion as the primary means of increasing production capacity. Only when they experience 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 within the same year of being hit by a positive shock.

We conduct a test to support our argument. If firms could respond within the same year as the positive shock hits, then land purchases made in the second half of the year would likely be a result of the shock, while purchases made in the first half of the

[20] 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 τ.

year would be more likely due to a positive shock from the previous year. Thus, when matching firms based on characteristics in the previous year, the potential positive bias from the matched sample would be greater for firms that bought land in the second half of the year. However, Table 3 Column (2) does not support this prediction. Here, we interact the treatment effect with a dummy H2 that equals one for firms that bought land in the second half of the year and zero otherwise. The treatment effect is similar, whether firms purchased the land in the first or second half of the year.

Lastly, we discuss one econometric issue regarding panel imbalance. Firms enter and exit our panel due to data linkage issues. We use firm names as firm identifiers, so name changes or name reporting inconsistencies can lead to panel imbalance if we fail to track a firm over time. Panel imbalance can also arise due to censoring when firm sales fall below a threshold 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.6, we study the causes of panel imbalance and conclude the imbalance is largely due to idiosyncratic data linkage issues. We also find evidence that a modest amount of imbalance is due to censoring, which we argue makes our estimates of land-purchase treatment effects conservative.

4.2.2 Firm Tax Estimation

We now calculate the marginal tax revenues generated by firms' land purchases. The most important taxes paid by industrial firms are value-added taxes (VAT) and corporate income taxes, both of which are approximately linear functions of the firm's value added.[21] Land purchases not only increase tax payments by land-purchasing firms, but also by firms on the supply chain. Assuming a homogeneous relationship between taxes and value added across firms, the total increase in taxes paid by all firms due to a single firm's land purchase equals the total increase in value added times the effective tax rate.

We approximate the total increase in value added to the economy (due to the land purchase) by the total increase in sales of that land-purchasing firm. By definition, the sales of the land-purchasing firm equal the sum of the value added by all *upstream* firms in the treated firm's supply chain, and hence we will miss the externality effects on other firms in the economy, such as downstream firms and competing firms. To sign the externality, Online Appendix B.8 presents a simple model with perfect competition, building on Hulten (1978) and Baqaee and Farhi (2019). Our analysis shows the increase in land buyers' output will overestimate changes in total output, if more input purchases

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

by the land buyer following its land purchase can cannibalize other firms' input purchases. However, firms typically have some idle capacity and hence it is not clear whether and to what extent such input cannibalization takes place. As far as we know, this remains an open question in this literature; we will leave this to future studies.

What remains is to estimate effective tax rates. We estimate these by regressing accumulated VAT payment on accumulated value added (i.e., sales) using the annual sample of industrial firms. Averaging across firms, we see a pretty linear relationship: 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.

Finally, we obtain the marginal effects of land purchases on tax revenues, by multiplying the tax rate of 17.87% with the DID estimate of the effect of land purchases on sales revenue, from column (1) of Table 3. Recall we have assumed that incremental tax cash flows start one year after the sale of industrial land. So for an industrial land sale in year $t-1$ (i.e., at the beginning of year t), the industrial tax cash flows in year s are:

$$\mathrm{Tax}^{ind}_{t-1,s} = 636.2 \times 17.87\% = 113.6\ \mathrm{RMB/m^2},\ \text{for } s-t \in \{0,1,2\} \tag{16}$$

$$\mathrm{Tax}^{ind}_{t-1,s} = 1199 \times 17.87\% = 214.2\ \mathrm{RMB/m^2},\ \text{for } s-t > 2 \tag{17}$$

4.2.3 Complementary Evidence

Our estimates of tax revenues 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 effect of land sales on taxes to the average VAT per square meter of land. For each province during our sample period, we calculate average VAT per square meter of land as total VAT revenue from China Tax Yearbook divided by total industrial land size from China City Construction Yearbook.[22] Appendix Figure A.6a shows the average VAT income per square meter of land for each province in 2011, right after the 2007–2010 sample period used to estimate the marginal taxes on industrial land. Across all provinces, the simple average VAT income per square meter of land is 332 RMB/m^2. This has the same magnitude as, though is slightly larger than, the long-run (marginal) tax revenue per square meter of land, 214.2 RMB/m^2 in Eq. (17).

[22]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.

Official guidance on minimum required tax on industrial land. For a second source of data on tax income, we use the government's direct guidance on the "required minimum" tax paid by firms operating 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 along certain dimensions (e.g., a green land ratio).[23] Some provincial land bureaus modified the guidelines by adding additional requirements on firms' tax payments, with Jiangsu province being the first to explicitly impose an industry-specific 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 province for manufacturing industries. The minimum tax requirement for most industries is around 100 RMB/m^2. If we average across industries using the industrial composition of land sales during 2007–2010 as the weight, we find an average minimum tax requirement of 113.6 RMB/m^2. Our marginal tax estimate of 214.2 RMB/m^2 accords with these minimum requirements.

4.3 Residential Tax Estimation

As in the estimation of industrial taxes, residential development will generate taxes not only from home developers that acquire the land, but also from upstream suppliers selling intermediate inputs to developers. The tax structure of home developers is different from manufacturers in terms of tax items and tax rates and we will estimate a distinct tax rate paid by home developers. 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 t, residential tax revenues are temporary, and we need to take a stance on their timing. In practice, some developer taxes (e.g., deed taxes and the stamp tax) are paid at the time of 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, i.e., $\mathsf{Tax}^{res}_{t,s} = \mathbf{1}_{s=t+1} \times \mathsf{ResTax}_s$ with

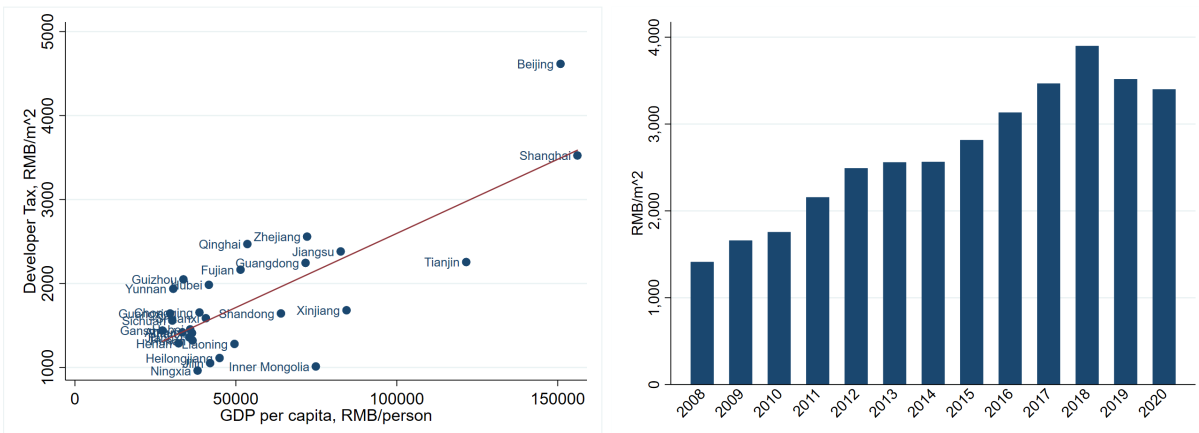
[23]Other restrictions are on the amount of fixed investment, floor ratio, the fraction of land for buildings and construction, and the fraction of land for offices and utilities.

$\mathtt{ResTax}_s$ denoting the residential taxes per square meter of residential land in year s.[24]

We calculate the tax revenue per square meter of land collected from residential land development in city c and year t as:

$$\mathtt{ResTax}_{c,t} = (P^h_{c,t} \times \mathtt{DevTaxRate}_t + \mathtt{Cost}_{c,t} \times \mathtt{IndTaxRate}) \times \mathtt{FloorRatio}_c, \tag{18}$$

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



(a) Prov. Residential Tax vs GDP Per Capita

(b) Residential Tax over Time

Figure 3: Residential Tax Estimates Summary.

Note: Panel (a) plots the province-level average residential taxes during 2008–2020 against the average GDP per capita during 2007–2019, both taken as a simple average across cities and years for each province. Panel (b) shows the average residential tax estimates across cities for each year from 2008 to 2020.

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.[25] Figure A.7 in the Online Appendix shows the relationship between the developers' annual taxes against their sales. The relationship is close to linear for any year, suggesting that $\mathtt{DevTaxRate}_t$ is roughly

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

[25]Since May 1, 2016, home developers start to pay 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.

independent of developer size. The intermediate cost $\mathsf{Cost}_{c,t}$ is the average value reported by local developers to China's National Bureau of Statistics. We measure $\mathsf{FloorRatio}_c$ using the area-weighted average value of all residential land parcels sold in city c during 2007–2019; there is little variation in the city-level floor ratio over time.

Figure 3 Panel (a) shows the strong positive correlation between GDP per capita and residential tax per square meter of land across different provinces. Panel (b) shows that the average amount of residential taxes is increasing over time.

4.4 IRR^{ind} Estimates

In this section, we use the framework in Section 3 to calculate IRR^{ind}. We first focus on 2007–2010, the sample period based on which we estimate the industrial tax revenues. We then provide various robustness discussions, and finally extend the methodology to calculate IRR^{ind} estimate over time.

4.4.1 IRR^{ind} during 2007–2010

Recall that the industrial tax estimates are at the national level and based on land sold during 2007–2010. We calculate national average values of the industrial land discounts and residential tax gains from residential land, by taking the weighted averages of $\mathsf{IndDisc}_{c,t}$ during 2007–2010 and $\mathsf{ResTax}_{c,t}$ during 2008–2011, weighted by the area of land purchased by treated firms in that city-year. We find that the weighted-average industrial land discount during 2007–2010 is 1012.83 RMB/m^2, and the weighted-average residential tax during 2008–2011 is 2367.01 RMB/m^2. Combining them with the estimates of industrial tax revenues, which are 113.6 RMB/m^2 in the first two years given by Eq. (16) and 214.2 RMB/m^2 thereafter given by Eq. (17), we calculate the government IRR in Eq. (2) to be $\mathsf{IRR}^{ind} = 5.80\%$.

A key takeaway from our paper is that our estimate of IRR^{ind} is not smaller than most estimates of government discount rates or the cost of capital in the literature, which we call r^{gov}. We proxy the city government's cost of capital using the issuance yield of municipal corporate bonds (MCBs, or Chengtou Bonds in Chinese). MCBs are bonds issued by local government financial vehicles (LGFVs), which are state-owned enterprises, to support infrastructure investment at both provincial and city levels.[26] Since the "RMB four-trillion stimulus plan," China's response to the global financial crisis in 2009–2010, MCBs have become the major financing source for Chinese city governments besides

[26] As explained in Chen et al. (2020), MCBs have the implicit backing of the corresponding city government (hence the name municipal), but in a strict legal sense they are issued by LGFV entities just like other regular corporations (hence corporate).

Table 4: Industrial Discount, Tax and IRR^{ind}

	IndDisc	Tax^{ind}		Tax^{res}	IRR^{ind}
Baseline	1012.83	113.67	214.23	2367.01	5.80%
Exclude Five-Yr-Plan-Targeted industries	991.55	98.89	171.77	2283.77	4.89%
Full Tax Deduction	1012.83	85.25	214.23	2367.01	5.58%
Two-year gap of $DevTax$	1012.83	113.67	214.23	2749.95	5.26%
Combination of three adjustments	991.55	74.17	171.77	2691.09	4.24%

Note: This table shows the industrial land discount estimates during 2007–2010, the tax benefits, and the corresponding IRR^{ind}. We aggregate the city-year level industrial discounts and developer taxes to the national level, all using the weight of the area of land purchased by the treated firms in that city-year when estimating Column (1) Table 3. We conduct robustness checks by excluding industries that were ever targeted by the Five-Year Plan (the second row), deducting the maximum possible tax rebates of 25% in the first five years (the third row), assuming the developer tax cash flow occurring two years following 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 the land area purchased by firms in nontargeted industries to match the industrial tax estimation.

selling land directly (Bai et al., 2016; Chen et al., 2020), and their market-determined yields reflect the city governments' fiscal conditions.[27]

We find that our estimate of IRR^{ind} is comparable to city governments' cost of capital r^{gov}, which ranges from 3.5% to 7.5% with an average value of 5.0%. In other words, for the project per se, industrial land does not appear to be a nonprofitable investment given city governments' costs of capital. If a city government borrowed using MCBs at r^{gov} and used this revenue to sell one piece of land as industrial rather than residential and make IRR^{ind}, it would almost break even on the project. As we discuss in Section 3.3, if we take into account price impacts on other land sales, the comprehensive return of industrial land supply from the governments' perspective should only be higher, which implies that overall, governments do not lose money when selling land as industrial rather than as residential.

As we discuss in Section 3.3 and formally show in Appendix A, this result also indicates that under the assumption of competitive land demand, the land allocation between industrial and residential uses is close to efficient. The efficient allocation result is more

[27] We do not use the yields of municipal bonds for three reasons. First, official municipal bonds (i.e., those issued by Chinese local governments directly) were rather limited in supply before Beijing launched the second major tax reform in 2014. Second, after 2015, municipal bonds are explicitly guaranteed by the central government, which removes any risk premia associated with fiscal conditions of municipalities. Third, municipal bonds are subject to strict issuance quotas, and hence do not serve as the marginal financing method for city governments.

likely an incidental result shaped by various deviations from a benchmark scenario that have opposite effects. Some deviations will favor residential against industrial land supply and lead to a higher IRR—e.g., local official myopia, intergovernmental tax sharing. Other deviations may lead to the opposite and a lower IRR—e.g.,the pursuit of nonpecuniary benefits from industrial development, the market power of local governments in the residential land market. Our findings indicate that, over the course of our sample period, deviations from the frictionless benchmark appear to balance each other out in equilibrium.

Contrary to some researchers' assumption that the tax revenues are too small to matter for land allocation decisions, our result also suggests the quantitative significance of the long-run tax revenues. In Section 5, we will provide further evidence suggesting that tax consideration does seem to affect the local government land allocation decisions. The evidence is based on predictions that *cannot* be easily explained when long-run tax revenues do not matter for land allocation decisions.

4.4.2 Robustness Checks

We conduct a number of robustness checks on our estimates of $\mathrm{IRR}^{\mathrm{ind}}$. First, we calculate $\mathrm{IRR}^{\mathrm{ind}}$ 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 2006–2015 (Cen et al., 2021). This addresses concerns that the government may be subsidizing targeted industries through other favorable policies, causing $\mathrm{IRR}^{\mathrm{ind}}$ to be biased upward for firms in these industries, as we have ignored these policies' costs.[28] We estimate $\mathrm{IRR}^{\mathrm{ind}}$ for targeted industries to be 6.11% (unreported), which is indeed modestly higher than the IRR of 4.89% for nontargeted industries. However, accounting for industrial policy–targeted industries does not substantially affect our IRR estimates as 4.89% is still comparable to the range of usual MCB yields.

Second, local governments occasionally offer tax rebates for new firm entrants in the first few years where they operate. The third row of Table 4 shows how our IRR estimate changes if we assume the most conservative case, that firms receive a 25% tax rebate in the first five years of their existence. This also reduces our IRR estimate only modestly, from the baseline level of 5.80% to 5.58%.

Third, we consider an alternative assumption on the timing of the residential tax cash flows, i.e., residential taxes all occur two years following land acquisition. The estimated

[28] 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.

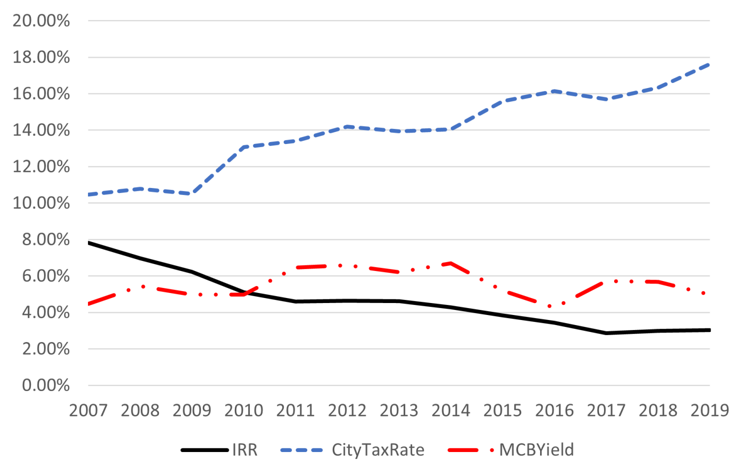


Figure 4: Industrial Discount and IRR

Note: This figure plots: (1) the time series of IRR^{ind} (black solid line), calculated by holding the tax benefits constant as in Eq. (16) and (17) and using the yearly estimates of industrial discounts and developer taxes; (2) the effective tax rates that accrue to the city governments (blue dotted line), estimated by regressing the annual change of the city government fiscal revenues plus central transfers on the annual change of the city GDP; and (3) the average MCB yield (red dash-dotted line), calculated as MCB issuance yield weighted by issuing amount for each year.

average residential taxes increase to 2749.95 $\mathrm{RMB}/\mathrm{m}^2$, and the IRR reduces modestly to 5.26% as shown in the fourth row.

In the last row, we consider the two subsidy policies together and the alternative timing of residential tax cash flows and find the IRR for nontarget industries to be 4.24%, which is still comparable to the usual range of government discount rates.

4.4.3 Time Series of IRR^{ind}

Recall that the industrial discount estimates used in Table 4 are based on land transactions in 2007–2010, during which time we have high-quality data on industrial firms for our tax estimation. Changes in land market conditions and the government incentives may have moved the IRR since 2010. To get some sense for how the return of industrial land supply has evolved over time, we assume that industrial taxes per square meter of industrial land stay the same after 2010.[29] We can then use our yearly estimates of industrial land discounts and residential taxes (weighted similarly to the first row in Table 4) to calculate the corresponding IRR_t^{ind} year by year.

Figure 4 plots the time series of IRR^{ind} along with the city government's discount

[29]It is unclear whether the tax yield on land increases or decreases over time. On the one hand, the productivity of the economy improves, but on the other more land has been supplied over time.

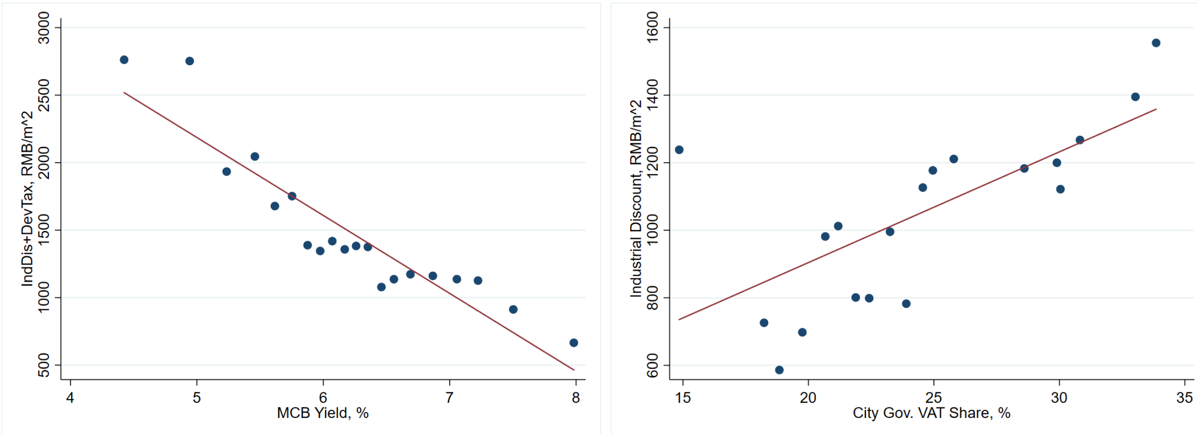
rates proxied by the average MCB yields. The $\mathrm{IRR}^{\mathrm{ind}}$ was stable during 2010 and 2015 and varied between 3.83% and 5.10%, both still comparable to the MCB yields. The $\mathrm{IRR}^{\mathrm{ind}}$ further decreased after 2015 and was about 3.03% in 2019, dippling slightly below government discount rates. As shown in Figure 4, the increasing trend of city governments' tax share in China—which favors industrial relative to residential land supply—could potentially explain the decreasing trend of $\mathrm{IRR}^{\mathrm{ind}}$. As will be shown in Section 5.2, this pattern also holds in the cross section.[30]

5 Tax Benefits and Land Supply

In Section 4, we showed that future tax revenues are quantitatively nontrivial as compared to the land prices. But do local governments' tax incentives have material effects on their land allocation decisions? To shed light on this question, we investigate two parameters closely related to the industrial tax benefits: the share of tax revenues internalized by city governments (κ_I) and the government cost of capital (r^{gov}). The first parameter captures how much weight the local governments put on future tax revenues and the second relates to how the local governments discount it. We will proxy κ_I with intergovernmental tax sharing. Although local governments may also internalize part of the tax revenues accruing to upper level governments, as long as they put more weight on their own tax share than on the upper level governments' share, their share of the tax revenues should be positively correlated with κ_I. For r^{gov}, we will use MCB yields as a measure for the local government borrowing cost. As the first set of evidence, in Figure 5, the left panel shows that municipal corporate bond yields are significantly negatively correlated with industrial discounts, and the right panel shows that the fraction of VAT accruing to city governments is significantly positively correlated with industrial discounts, both consistent with the predictions of our framework.

Before examining these two causal predictions in more details, one may argue that "myopic" local officials tend to ignore long-run industrial tax revenues in China. Though this might be the case for the upper-level leadership team in China, local officials at the grassroots level can be quite persistent. A unique feature of Chinese government personnel systems is that most government officials have to start from "the bottom" before being promoted step-by-step along the political hierarchy; such promotion usually occurs within the same county before reaching upper-level positions. For instance, for those who

[30] If we replace the total tax measures in Eq. (2) with the amount of tax that goes to the city government based on its annual tax share, the IRR will be more stable over time, i.e., it will only decrease by 1.72% from 2007 to 2019 as compared to a decrease of 4.78% in Figure 4.



(a) MCB Yields

(b) City Government's VAT Share

Figure 5: Industrial Discount, MCB Yield, and City Government Tax Share

Note: Panel (a) plots bin scatter of $\mathtt{IndDisc}_{ct}$ against the average yields of municipal corporate bonds issued by the governments in city c year t for the sample period 2007-2019; Panel (b) plots bin scatter of $\mathtt{IndDisc}_{c,t}$ against the city government's VAT share in year t for the sample period 2007-2019.

took office during 2006–2010, about 45% of the county party secretaries have previously worked as mayors of the same county, and 46% of the county mayors will continue to work as party secretaries of the same county. Considering most party secretaries and mayors will first work in the corresponding deputy positions, the total time that local officials work in leadership positions in the same county can be long enough for them to care about the long-run tax revenues.

5.1 Government Discount Rates

Panel (a) of Figure 5 provides suggestive evidence that governments with higher cost of capital have lower industrial discounts. A possible endogeneity concern is that certain forces may affect both MCB yields and industrial discounts, so this relationship cannot directly be interpreted as causal. To address this concern, 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.

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 to be conducted in 2009–2010. Local governments responded by increasing investment in infrastructure, which had long-lasting effects on the local government's fiscal position in the future and hence on future bond yields. Across different provinces, local officials' responsiveness depended on their tenure clock. Chen et al. (2020) show that cities in provinces whose governors were late in their term engage in more local infrastructure investment in 2009. Local government officials' tenure is plausibly related to investment choices in 2009 because the incentive to comply with the central government in general increases with the governor's term.[31]

Following Chen et al. (2020), we construct an instrument, $\mathsf{LateTerm}_c$ 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, $\mathsf{LateTerm}_c$ is negatively correlated with MCB yield in subsequent years, in particular during 2012–2019. 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 2012–2019 is 28.1.

The exclusion restriction for the instrument is that these fiscal changes are only correlated with the future industrial discounts through changes in MCB yields. In particular, the exclusion restriction requires that the size of the governments' land inventory, which is affected by $\mathsf{LateTerm}_c$, does not directly affect the choice of what mix of residential or industrial land to sell.[32] Moreover, to avoid the direct effect of governor term in 2009 on land allocation, we will apply the instrument to the sample starting from 2012. Chen et al. (2020) show that thanks to the anti-corruption campaign launched in 2012, there is negligible correlation between governor term in 2009 and in future years after 2012.

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

$$\mathsf{IndDisc}_{c,t} = \beta \times \mathsf{MCBYield}_{c,t} + \sum_{\tau} \gamma_\tau' \cdot \mathbf{1}_{t=\tau} \cdot [X^1_{c,2008}, X^2_{c,t}] + \epsilon_{c,t}, \tag{19}$$

where $\mathsf{MCBYield}_{c,t}$ is the average yield of MCB bonds issued by city c in year t and weighted by issuance amounts.[33] To separate our estimation sample from the potential

[31] 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).

[32] Chen et al. (2020) show that provinces with greater stimulus bank loans in 2009, due to future refinancing needs, experience faster MCB growth and more shadow banking activities during 2012–2015. 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.

[33] 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

direct effect of the governor's term in 2009, we estimate Eq. (19) based on the sample period 2012–2019. 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 $\mathtt{LateTerm}_c$ might affect the outcome variable and hence invalidate the exclusion restrictions.

Table 5 shows the results. The first three columns of Panel A show OLS estimation results; consistent with Figure 5, industrial discounts are negatively correlated with MCB yields in the cross section. In columns 4 and 5, we instrument $\mathtt{MCBYield}_{c,t}$ with $\mathtt{Lateterm}_c$; the effect of $\mathtt{MCBYield}_{c,t}$ is negative and significant. In column 6, when including the ex post conditions as controls, the IV coefficient estimate barely changes.[34]

In Panel B, we proceed to test whether municipal bond yields also affect the *quantities* of residential and industrial land sold, by replacing the dependent variable in Eq. (19) 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. In terms of magnitude, when MCB yield increases by 1%, annual industrial land supply will exceed residential land supply by 0.5 square meter per capita.

The finding implies that city governments' land allocation decisions can be entangled with their financial strength. If local governments in China have historically been financially constrained, they will sell more residential land and less industrial land, and such reallocation of land uses may have had a large impact on the country's industry structure such as the relative size of real estate and manufacturing sector. This knock-on effect of municipal finance on industrial structure deserves more attention from policy makers.

5.2 City Tax Shares

The city governments keep almost the entirety of their land sales revenue, but value-added, corporate income and business taxes are all shared between the city and upper-level governments. In this subsection, we investigate the relationship between industrial

of ChinaBond Urban Construction Investment Bond Yield-to-Maturity Curve.

[34] In Online Appendix C.2.2, with the same specification as Eq. (19), we also find a significant and negative causal effect of the MCB yields on the city's up-front developer taxes.

Table 5: 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, %	-577.5***	-345.4***	-259.8***	-1,823***	-2,534***	-2,558**
	(-9.105)	(-6.134)	(-5.349)	(-7.472)	(-3.013)	(-2.511)
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	0.326	0.448	0.550	-0.783	-1.978	-1.890
#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, %	-0.504**	-0.234	0.253**
	(-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, i.e., the average yields of MCBs weighted by the bond size. Panel A reports the effect on industrial land discount: Columns (1)-(3) report the OLS estimation results and Column (4)-(6) report the 2SLS estimation results where the City MCB yield is instrumented by $\mathtt{LateTerm}_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. Panel B reports the 2SLS estimation results for the industrial land supply relative to residential, all in sq.me. per 100 people. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

discounts and the share of value-added taxes that accrue to city governments.

In China, Beijing gets a uniform share of value-added taxes across provinces; the province-level government has discretion in setting how to split the remaining share between itself and the city-level governments, and there is variation in the share of VAT accrued to city governments in different provinces.[35] Although the actual share of VAT that accrues to the city governments may underestimate the extent to which the city governments internalize tax revenues from industrial land sales, our study only relies on the assumption that the city VAT share is at least positively correlated with the extent to which city governments internalize future tax revenues in their land allocation decisions.

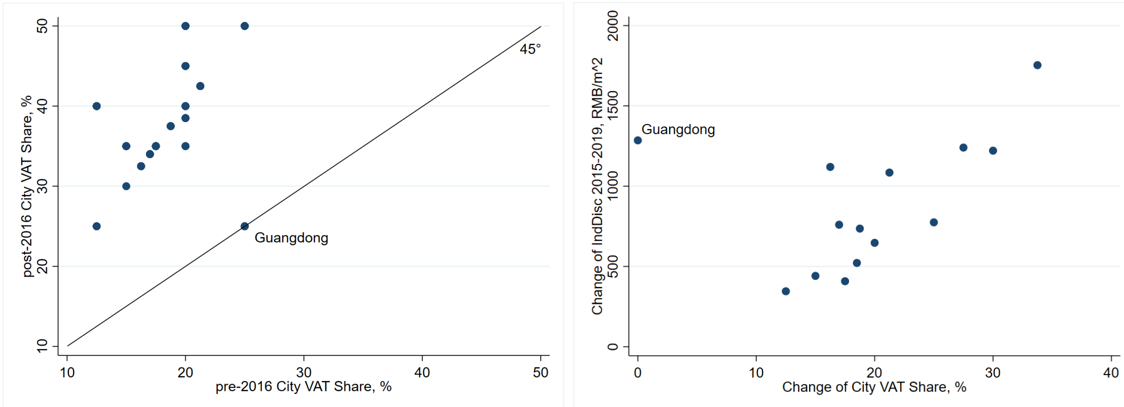
To present clean evidence on the causal effect of the city's tax share on the industrial discount, we analyze a change in tax-sharing schemes in 2016. Before May 1, 2016, the central government took 75% of the value-added taxes and the remaining 25% went to the provincial and city governments. On May 1, 2016, Beijing launched a major tax code change–the so-called "Business to Value-Added" program—which enlarged the coverage of value-added taxes. More relevant to our study, this reform modified the tax-sharing scheme, so that the share of value-add taxes retained by local governments increased from 25% to 50%.[36] Province-level governments would then decide how to split the incremental 25% of the value-added taxes between itself and city governments. The differential increase of the city's VAT share in 2016 provides an opportunity to test the effect of tax sharing on the industrial discounts.

City VAT Share and Industrial Discounts: Raw Data. Panel A in Figure 6 shows the pre-2016 city VAT share on the x-axis, and the post-2016 city VAT share on the y-axis. Most cities experienced an increase in their share, except for cities in Guangdong whose share remained at 25%; we will explain the special circumstance of Guangdong shortly. There is also substantial heterogeneity in the magnitude of the tax share increase across cities, allowing us to investigate how industrial discounts respond to their VAT shares. Indeed, Panel B in Figure 6 shows a binned scatterplot of the change in the industrial land discount from 2015 to 2018 relative to the city VAT share change in 2016. There is a strong positive correlation between the two variables (without counting cities in Guangdong).

In both panels of Figure 6 we observe that cities in Guangdong province appear to be outliers. Although they experienced zero increase in their share of VAT, the industrial land discount increased substantially from 2015 to 2018 in these cities. One possible explanation is that Guangdong implemented confounding policies that encouraged industrial land supply, and these policies did not exist in other provinces; see Online Appendix C.3 for more details on these unique land-related policies for Guangdong. For

[35] 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.

[36] 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.



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

Figure 6: Change of City VAT Share and Industrial Land Discount

Notes: Panel (a) plots the city government's share of VAT before and after 2016. Most cities within the same province receive the same share with very few exceptions. Panel (b) plots a binscatter of the change of city-level industrial land discount from 2015 to 2018 against the change of city VAT share.

these reasons we remove Guangdong from our analysis in the rest of this section.

Event Study on Industrial Discounts. We apply an event study analysis to study how local governments' land allocation decisions respond to these changes in city VAT shares:

$$y_{c,t} = \alpha_c + \gamma_t + \sum_{\tau \neq 2015} \beta_\tau \times \mathbf{1}_{t=\tau} \times \Delta VATShare_c + \varepsilon_{c,t}. \tag{20}$$

In Eq. (20), we use the year before the taxation change, 2015, as the base year. We also include interactions with years before 2015 to test the assumption of parallel trends between cities with differential treatment.

If city governments' land allocation decisions are indeed sensitive to tax revenues, then as the share of industrial tax revenues accruing to city governments increases, they should be willing to offer a higher industrial land discount (a lower IRR^{ind}). The estimation results reported in Table 6 support this hypothesis. We observe a significant and positive treatment effect on the industrial land discount in all years since 2016. Moreover, there was no significant difference between cities with differential treatment prior to 2016, which lends support to the parallel trends assumption underlying this difference-in-differences strategy.

In Columns (2)–(3), we investigate the industrial and residential land price separately. Consistent with our framework, we find that an increase in the share of industrial tax

Table 6: City VAT Share and Industrial Land Discount

Dep Var:		Price			Quantity		
		IndDisc	$(1-\lambda)p^{res}$	p^{ind}	(Ind-Res)/Pop	Res/Pop	Ind/Pop
		(1)	(2)	(3)	(4)	(5)	(6)
$\Delta VATShare \times$							
Year=	2012	-0.156	-1.965	-1.810	0.0162	-0.00284	0.0151
		(-0.0136)	(-0.188)	(-1.032)	(1.490)	(-0.568)	(1.270)
	2013	-7.514	-7.961	-0.447	0.00961	0.00719	0.0163
		(-0.927)	(-0.987)	(-0.461)	(0.931)	(1.284)	(1.535)
	2014	-1.192	-0.603	0.589	-0.00291	0.00284	-0.000958
		(-0.0790)	(-0.0390)	(0.605)	(-0.381)	(0.766)	(-0.127)
	2016	21.90***	20.66***	-1.245**	0.000433	-0.00641*	-0.00748
		(3.173)	(2.989)	(-1.978)	(0.0627)	(-1.721)	(-1.008)
	2017	43.42***	41.42***	-2.001***	0.0147*	0.00762	0.0215**
		(3.941)	(3.705)	(-2.605)	(1.762)	(1.483)	(2.210)
	2018	26.25**	25.10**	-1.148	0.0400***	0.00174	0.0410***
		(2.276)	(2.156)	(-0.855)	(3.679)	(0.308)	(3.392)
	2019	34.17***	33.84***	-0.325	0.00967	0.00164	0.0101
		(3.134)	(3.059)	(-0.266)	(0.976)	(0.322)	(0.968)
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		0.831	0.846	0.836	0.705	0.760	0.661
#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 land supply relative to residential. The sample consists of all the municipal cities (except those in Guangdong); the sample in Column (1)–(3) is smaller because we need industrial discount estimates from 2012–2019. The treatment variable, $\Delta VATShare$, is in percentage and the land supply is sq.me per 100 people. Standard errors are clustered by cities. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

revenues that accrue to the local government tends to increase residential land prices and decrease industrial land prices. The effect on residential land prices is quantitatively larger, likely because the levels of residential land prices are much higher.[37]

In Columns (4)–(6) of Table 6, we examine the impact of intergovernmental tax sharing on the quantities of industrial and residential land sold, by replacing the dependent variable in Eq. (20) with the difference between industrial and residential land supply per

[37] Although our primary interest is in the industrial discounts, the theoretical framework predicts that an increase in city governments' share of industrial taxes leads to an increase in the sum of industrial discounts and the developer taxes accruing to city governments. We confirm this in Online Appendix C.2.2.

capita. In Column (4), consistent with the first hypothesis, an increase in the tax share of the city government 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.

Our evidence on price is stronger than that on quantity. There are two possible mechanisms through which the industrial discount adjusts. First, since the government and the potential buyers negotiate the transaction price, buyers who know that more future taxes go to the local government may ask for a greater industrial discount; this mechanism does not even require quantity adjustment. Second, and perhaps more important, as mentioned in Section 2 the quantity adjustment may not occur in the short run given the planning constraint, implying that land allocation adjustment might occur in the future. However, because of the durable-goods nature of land, forward-looking prices (and hence industrial discounts) will immediately adjust.

6 Conclusion

In this paper, we analyze the industrial land discount in the Chinese land market. Contrary to the conventional wisdom, the return of supplying industrial instead of residential land, accounting for all future tax revenues, lies within the usual range of government discount rates proxied by MCB yields during 2007–2010. This result suggests that governments do not lose money when supplying land as industrial rather than as residential. It also indicates that the land allocation between industrial and residential uses, an outcome jointly shaped by local government incentives and land market conditions, is close to efficient under the assumption of competitive land demand. In the cross section, we also find suggestive evidence that local governments' tax incentives have a material effect on land allocation.

Our results have implications for understanding the drivers of land prices in China and how they are linked to government incentives such as 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 carefully designed to counteract the effect of other forces such as 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.

References

Adelino, Manuel, Igor Cunha, and Miguel A Ferreira, 2017, The economic effects of public financing: Evidence from municipal bond ratings recalibration, *Review of Financial Studies* 30, 3223–3268.

Agrawal, Ashwini K, and Daniel Kim, 2021, *Municipal bond insurance and the US drinking water crisis* (LSE Financial Markets Group).

Altshuler, Alan A, and Jose A Gomez-Ibanez, 2000, *Regulation for revenue: The political economy of land use exactions* (Brookings Institution Press).

Amornsiripanitch, Natee, 2022, Bond insurance and public sector employment .

Bai, Chong-En, Chang-Tai Hsieh, and Zheng (Michael) Song, 2016, The long shadow of China's fiscal expansion, *Brookings Papers on Economic Activity* 129–165.

Bai, Yan, Keyu Jin, and Dan Lu, 2019, Misallocation under trade liberalization, Technical report, National Bureau of Economic Research.

Baker, Andrew C, David F Larcker, and Charles CY Wang, 2022, How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370–395.

Baqaee, David Rezza, and Emmanuel Farhi, 2019, The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem, *Econometrica* 87, 1155–1203.

Berk, Jonathan, and Peter DeMarzo, 2017, *Corporate Finance: Global Edition* (Pearson).

Blöchliger, Hansjörg, Christian Hilber, Olivier Schöni, and Maximilian von Ehrlich, 2017, Local taxation, land use regulation, and land use: A survey of the evidence .

Blundell, Richard, and Monica Costa Dias, 2000, Evaluation methods for non-experimental data, *Fiscal studies* 21, 427–468.

Burnes, Daria, David Neumark, and Michelle J White, 2014, Fiscal zoning and sales taxes: Do higher sales taxes lead to more retailing and less manufacturing?, *National Tax Journal* 67, 7–50.

Cai, Hongbin, J. Vernon Henderson, and Qinghua Zhang, 2013, China's land market auctions: Evidence of corruption?, *RAND Journal of Economics* 44, 488–521.

Cen, Xiao, Vyacheslav Fos, and Wei Jiang, 2021, A race to lead: How Chinese government interventions shape the US-China production competition, Working paper, Columbia University.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, 2019, The effect of minimum wages on low-wage jobs, *Quarterly Journal of Economics* 134, 1405–1454.

Cestau, Dario, Burton Hollifield, Dan Li, and Norman Schürhoff, 2019, Municipal bond markets, *Annual Review of Financial Economics* 11, 65–84.

Chen, Ting, and James Kai-sing Kung, 2019, Busting the "princelings": The campaign against corruption in China's primary land market, *The Quarterly Journal of Economics* 134, 185–226.

Chen, Ting, Laura Liu, Wei Xiong, Li-An Zhou, et al., 2017, Real estate boom and misallocation of capital in china, *Work. Pap., Princeton Univ., Princeton, NJ* 9.

Chen, Zhuo, Zhiguo He, and Chun Liu, 2020, The financing of local government in China: Stimulus loan wanes and shadow banking waxes, *Journal of Financial Economics* 137, 42–71.

Cheshire, Paul C, and Christian AL Hilber, 2008, Office space supply restrictions in Britain: The political economy of market revenge, *Economic Journal* 118, F185–F221.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille, 2020, Two-way fixed effects estimators with heterogeneous treatment effects, *American Economic Review* 110, 2964–2996.

Dehejia, Rajeev H, and Sadek Wahba, 1999, Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs, *Journal of the American Statistical Association* 94, 1053–1062.

Deng, Yongheng, Yang Tang, Ping Wang, and Jing Wu, 2020, Spatial misallocation in Chinese housing and land markets, Working Paper 27230, National Bureau of Economic Research Working Paper.

Deshpande, Manasi, and Yue Li, 2019, Who is screened out? Application costs and the targeting of disability programs, *American Economic Journal: Economic Policy* 11, 213–248.

Fan, Jianyong, Jiawei Mo, and Jipeng Zhang, 2015, Housing models and urbanization in China: Empirical research from the perspective of land supply, *Social Sciences in China (in Chinese)* 44–63.

Giesecke, Oliver, and Haaris Mateen, 2022, Local governments' response to fiscal shocks: Evidence from Connecticut, *Available at SSRN 4185090* .

Harvey, Jack, and Ernie Jowsey, 2019, *Urban land economics* (Bloomsbury Publishing).

Heinrich, Torsten, Jangho Yang, and Shuanping Dai, 2020, Levels of structural change: An analysis of China's development push, Technical report.

Henderson, J Vernon, Dongling Su, Qinghua Zhang, and Siqi Zheng, 2022, Political manipulation of urban land markets: Evidence from China, *Journal of Public Economics* 214, 104730.

Hsieh, Chang-Tai, and Peter J Klenow, 2009, Misallocation and manufacturing TFP in China and India, *Quarterly Journal of Economics* 124, 1403–1448.

Hulten, Charles R, 1978, Growth accounting with intermediate inputs, *Review of Economic Studies* 45, 511–518.

LaPoint, Cameron, 2022, Property tax sales, private capital, and gentrification in the U.S., *Private Capital, and Gentrification in the US (September 15, 2022)* .

Lei, Xiaoyu, and Liutang Gong, 2014, Industrialization and urbanization based on land supply, *Management World (in Chinese)* 29–41, ZSCC: 0000042.

Li, Hongbin, Prashant Loyalka, Scott Rozelle, and Binzhen Wu, 2017, Human capital and China's future growth, *Journal of Economic Perspectives* 31, 25–48.

Li, Ming, 2019, Information and corruption: Evidence from China's land auctions, Working paper.

Lin, George CS, and Fangxin Yi, 2011, Urbanization of capital or capitalization on urban land? Land development and local public finance in urbanizing China, *Urban Geography* 32, 50–79.

Liu, Chang, and Wei Xiong, 2020, China's real estate market, in *The Handbook of China's Financial System*, 183–207 (Princeton University Press).

Liu, Ernest, 2019, Industrial policies in production networks, *Quarterly Journal of Economics* 134, 1883–1948.

Liu, Qing, and Yi Lu, 2015, Firm investment and exporting: Evidence from China's value-added tax reform, *Journal of International Economics* 97, 392–403.

Liu, Xiaoping, Guohua Hu, Yimin Chen, Xia Li, Xiaocong Xu, Shaoying Li, Fengsong Pei, and Shaojian Wang, 2018, High-resolution multi-temporal mapping of global urban land using Landsat images based on the Google Earth Engine Platform, *Remote Sensing of Environment* 209, 227–239.

Nie, Huihua, Ting Jiang, and Rudai Yang, 2012, A review and reflection on the use and abuse of Chinese industrial enterprises database, *World Economy (in Chinese)* 142–158.

Oster, Emily, 2019, Unobservable selection and coefficient stability: Theory and evidence, *Journal of Business & Economic Statistics* 37, 187–204.

Pinardon-Touati, Noémie, 2021, The crowding out effect of local government debt: Micro- and macro-estimates .

Posenau, Kelly, 2021, Debt and water: Effects of bondholder protections on public goods, Technical report, Working Paper.

Quigley, John M, and Steven Raphael, 2005, Regulation and the high cost of housing in California, *American Economic Review* 95, 323–328.

Ru, Hong, 2018, Government credit, a double-edged sword: Evidence from the China Development Bank, *Journal of Finance* 73, 275–316.

Schmenner, Roger W, 2005, Look beyond the obvious in plant location, *Journal of Econometrics* 125, 305–353.

Smith, Jeffrey A, and Petra E Todd, 2005, Does matching overcome LaLonde's critique of nonexperimental estimators?, *Journal of Econometrics* 125, 305–353.

Tan, Ya, Zhi Wang, and Qinghua Zhang, 2020, Land-use regulation and the intensive margin of housing supply, *Journal of Urban Economics* 115, 103199.

Tang, Maogang, Ruihan Zhang, Zhen Li, and Baijun Wu, 2021, Assessing the impact of tradable discharge permit on pollution reduction and innovation: Micro-evidence from Chinese industrial enterprises, *Environment, Development and Sustainability* 1–23.

Tao, Ran, Fubing Su, Mingxing Liu, and Guangzhong Cao, 2010, Land leasing and local public finance in China's regional development: Evidence from prefecture-level cities, *Urban Studies* 47, 2217–2236.

Tian, Wenjia, Zhi Wang, and Qinghua Zhang, 2022, Transaction mechanism and industrial land allocation efficiency in China: Evidence from the 2007 auction reform, *Available at SSRN 4016228* .

Wu, Jing, Yongheng Deng, and Hongyu Liu, 2014, House price index construction in the nascent housing market: The case of China, *Journal of Real Estate Finance and Economics* 48, 522–545.

Wu, Min, and Li-An Zhou, 2015, Tax sharing rates among sub-provincial governments in China: Facts and explanation, *Journal of Financial Research (in Chinese)* 10, 64–80.

Yi, Hanyi Livia, 2021, Financing public goods, *Available at SSRN 3907391* .

Zhang, Jinyuan, 2021, The impact of public pension deficits on households' investment and economic activity, *Available at SSRN 3918170* .

Zhang, Li, Ming Lu, and Yali Liu, 2022, Tax incentives and supply structure of commercial and residential land, *China Economic Quarterly (in Chinese)* 22, 1425–1446.

Zhao, Aidong, Huub Ploegmakers, Ary Adriansyah Samsura, Erwin van der Krabben, and Xianlei Ma, 2024, Price competition and market concentration: Evidence from the land market in China, *Cities* 144, 104631.

Online Appendix

A A Model of Land Allocation

In this section, we will consider a framework with a most general specification about the local governments' objectives when making land allocation decisions. We will characterize the market equilibrium and discuss the economic meanings of IRR^{ind}.

We will take the view of local governments who, as we have argued in Section 2, are the one that decide the local land allocation. We will first show that the equality between IRR^{ind} and the government discount rate can be linked to the efficiency of land allocation and then study the relationship under various assumptions about the government objectives and land market conditions.

Setup. The government allocates a fixed amount of land inventory $\bar{L}$ 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 as $f(L_I)$ and the residential sector as $g(L_R) - P_R \cdot L_R$. Note that land is counted as capital for the industrial sector and material input for the residential sector. $f(L_I)$ occurs annually while $g(L_R) - P_R \cdot L_R$ is one-time. Assume both $f(L_I)$ and $g(L_R)$ are 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 as a function of the value-added to be τ_R (τ_L) and the share that is internalized by the local governments to be κ_R (κ_L) 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, $\kappa_L \cdot \tau_L \cdot f(L_I)$, 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 the leadership positions and do not care about the tax revenues going forward. Denote the discount rate to be r. The present value of the future industrial tax revenues internalized by the myopic local official is then

$$\kappa_L \cdot \tau_L \cdot f(L_I) \sum_{t \geqslant 1} (\frac{\delta}{1+r})^t = \kappa_L \cdot \tau_L \cdot f(L_I) \frac{\delta}{1+r-\delta}$$

The last component is the non-pecuniary benefits. Both industrial and residential land supply can promote economic growth and increase employment, which may enter the local officials' objectives either due to their altruism or the linkage with their political career. 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 the industrial land supply and $\lambda_R \cdot (f(L_R) - P_R \cdot L_R)$ from the residential land supply.

On the demand side, we will assume competitive market demand and constant price elasticity of demand, σ_R and σ_I. The market demand for land is largely competitive since 2007 as all the residential and industrial land supply has to be made through public auctions whenever there are no less than two interested buyers.

As in Section 3, we define the IRR 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

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

The numerator is the perpetuity tax revenues from the marginal industrial land supply. The denominator is the tax revenues from the marginal residential land supply plus the industrial discount.[38] Importantly, the IRR^{ind} does not incorporate the price impacts of the marginal land supply on other land sales. Therefore, it is not the return of adjusting land zoning on the margin from the perspective of the local governments.

IRR and Market Efficiency.

Proposition 1. *Assuming competitive land demand, land allocation is efficient if and only if* $IRR^{ind} = r$.

Proof. Assuming competitive land demand, the marginal profit must be zero, which implies

$$g'(L_R) = P_R, \quad f'(L_I) \cdot \frac{1-\tau_I}{r} = P_I$$

[38] For simplicity, we have ignored the λP_R in Eq. 1 which is inconsequential and can be easily incorporated by adjusting notations.

Substitute the two conditions into the definition of IRR^{ind}, we then have

$$\mathrm{IRR}^{ind} = r \iff g'(L_R) = \frac{f'(L_I)}{r} \tag{21}$$

Eq. (21) suggests that the marginal surplus of residential land supply is equal to the present value of the marginal surplus of industrial land supply. This is exactly the condition for efficient land allocation. □

Intuitively, $\frac{\tau_I \cdot f'(L_I)}{r}$ is the marginal willingness to pay of the private sector to the local government for one piece of industrial land, and $\tau_R(g'(L_R) - P_R) + P_R - P_I$ is the marginal willingness to pay of the private sector to the local government for changing the land zoning from industrial to residential. When $\mathrm{IRR}^{ind} = r$, the two willingness equals, which means on the margin, industrial land and residential land generates the same net surplus or profits to the private sector. Different from other markets where the seller only collects the product price, we need to count both the land price and the tax revenues due to the joint role of the local governments as the land seller and the tax collector.

To characterize the market equilibrium, consider the local governments' optimization problem:

$$\begin{aligned}
&\max_{L_I, L_R} \left(\frac{\delta}{1+r-\delta}\kappa_I \tau_I + \lambda_I\right) \cdot f(L_I) + L_I P_I + (\kappa_R \tau_R + \lambda_R) \cdot (g(L_R) - L_R P_R) + L_R P_R \\
&\text{s.t. } L_I + L_R = \bar{L},\ g'(L_R) = P_R,\ f'(L_I) \cdot \frac{1-\tau_I}{r} = P_I
\end{aligned} \tag{22}$$

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

$$W'(L_I) = \left(\frac{\delta}{1+r-\delta}\kappa_I \tau_I + \lambda_I + \frac{1-\tau_I}{r}(1-\sigma_I^{-1})\right) f'(L_I) - \left(1 - \sigma_R^{-1}(1 - \kappa_R \tau_R - \lambda_R)\right) g'(L_R) \tag{23}$$

The market equilibrium 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) and do not have market power in the land markets ($\sigma_R = \sigma_I = \infty$), then in equilibrium,* $\mathrm{IRR}^{ind,\star} = r$.

Proof. Plug the parameters into Eq. (23), we get $\frac{f'(L_I^\star)}{r} = g'(L_R^\star)$. Plug this condition and

$g'(L_R) = P_R$, $f'(L_I) \cdot \frac{1-\tau_I}{r} = P_I$ into the definition of IRR^{ind}, we get $IRR^{ind,\star} = r$. □

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, and do not have market power over local land market, the market equilibrium will lead to 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, none of these conditions are likely to hold 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-supply or over-supply of industrial land.

Proposition 3. $L_I^\star$ *will increase and* $IRR^{idd,\star}$ *will decrease when* λ_I *increases and* σ_R *decreases;* $L_I^\star$ *will decrease and* $IRR^{idd,\star}$ *will increase when* δ *decreases,* κ_I *decreases,* σ_I *decreases and* λ_R *increases.*

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. □

Proposition 3 states how the equilibrium land allocation and IRR^{ind} would change under some reasonable 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, or when the local governments have market power in the industrial land market. Therefore, in equilibrium, it is uncertain whether the industrial land is under- or over-supplied. Our results in Section 4 suggests that during 2007-2010, all these different deviations likely counteract each other and the land allocation between industrial and residential uses was close to be efficient.

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.6.

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.

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.

B.2 Estimating λ

We first estimate the "non-standard" compensation to local land occupants (such as "resettlement cost for demolition"). As the "non-standard" nature of this type of cost implies, the data on it is not available at the land parcel level. Therefore, we choose to infer it as a proportional cost from the aggregate data of budget accounts of local government-managed funds. In particular, we calculate the fraction λ_1 of the land sales which must be shared with local land occupants, as the quotient of the budgeting total expenditure on "Compensation for Using Land and Removing" of the budgeting total revenue on "Sale Receipt of State-owned Land-use Rights".[39] Since we only have data on those numbers between 2010–2014 and we need to use lagged budget revenue to adjust for the time lag between land reserving and land sales, in the end we get $\lambda_1 = 0.28$ using

[39]Note that those items do not distinguish between industrial and residential, but they're generally dominated by residential land, so this is as good an approximate as we can get.

the averages between years 2010–2012, which is in the middle of our data sample.[40]

For the auxiliary cost associated with providing public services to new residences,[41] we also impose a linear cost structure: if the parcel is sold as residential land, an additional fraction λ_2 of the land must be allocated to build schools. We estimate λ_2 by regressing the total area of educational lands on total area of residential lands across different cities, both sold during 2007-2010 and scaled by city population in 2010, after controlling for province fixed effects. The time window 2007-2010 is chosen because we estimate the marginal output of land input based on land sold in 2007-2010. We also conduct the same regression for time interval 2011-2019. To explore potential heterogeneity of λ_2, we divide the cities into three groups based on the average price of land sold during 2007-2019.

Table A.2 shows estimates of λ_2. In 2007-2010, for every 100 square meters of residential land, the city government will supply about 8 square meters of land for schools. There is not much heterogeneity across cities with different land price levels. In 2011-2019, the supply of education land seems to have doubled for cities with high and medium price levels, but remains mostly unchanged for the cities with low price levels.

The estimates above provide us with the additional cost factor associated with residential land $\lambda = 1 - \frac{1-\lambda_1}{1+\lambda_2} = 1/3$.

Table A.2: Lambda Estimates

	Sample Period	
Price Tier	2007-2010	2011-2019
High	0.073***	0.171***
	(4.231)	(7.404)
Medium	0.079***	0.146***
	(6.666)	(7.231)
Low	0.094***	0.077**
	(6.386)	(2.798)
Total	0.087***	0.114***
	(10.737)	(8.695)

Note: Price tiers are divided based on the 1/3 and 2/3 quantile of the distribution of city-level average land price between 2007-2019. Robust t statistics clustered at province level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[40] There is also no data on the time lag between land reserving and land sales, so we chose to take the averages of lagging one to three years. Specifically, we take the total budget compensation between 2010 and 2012, divide it by the total budget revenue between 2011-2013, 2012-2014, and 2013-2015, respectively, and finally take the average of these three ratios. Note that we see an increasing time trend in λ_1 within our limited sample; unfortunately, we don't have enough data to track the whole time trajectory of λ_1.

[41] See the 2012 Code for Planning Standards, Item 4.3.2.

B.3 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 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.

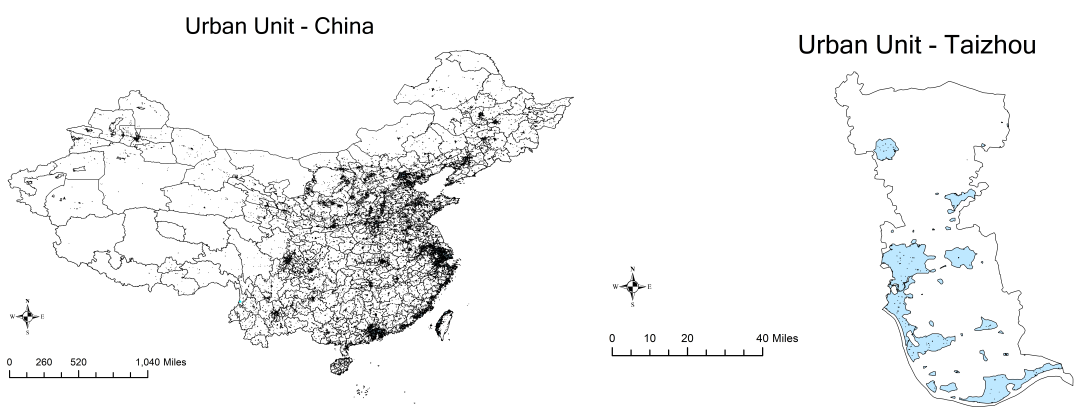


Figure A.1: Examples of Urban Units.

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.

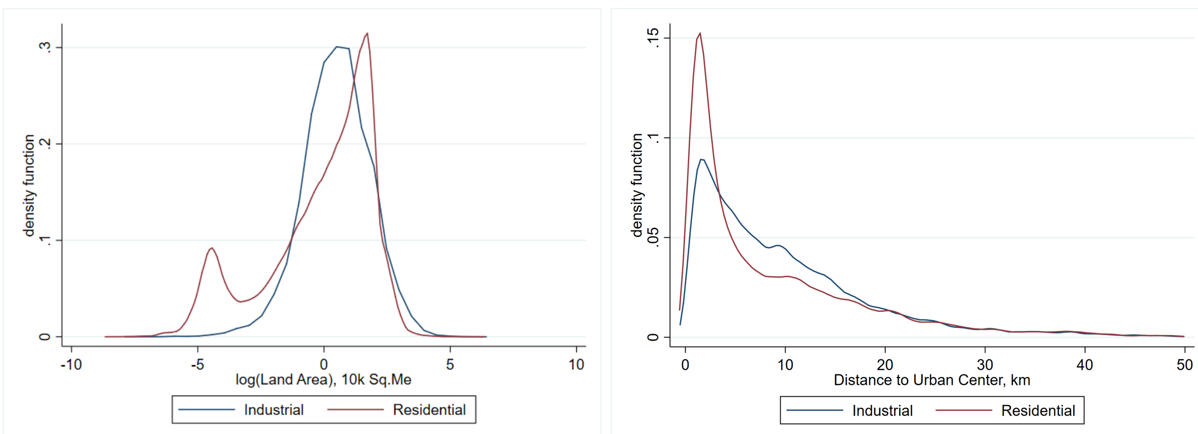
In Figure A.1, we first show the distribution of urban units throughout the country. A larger fraction of land is covered by these urban units in the more developed coastal areas, especially the Circum-Bohai Sea Region, the Yangtze River delta, and the Pearl River Delta. In Panel B we use Taizhou, a 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.4 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 (4) and (6) across different city-period samples.



(a) Land Area

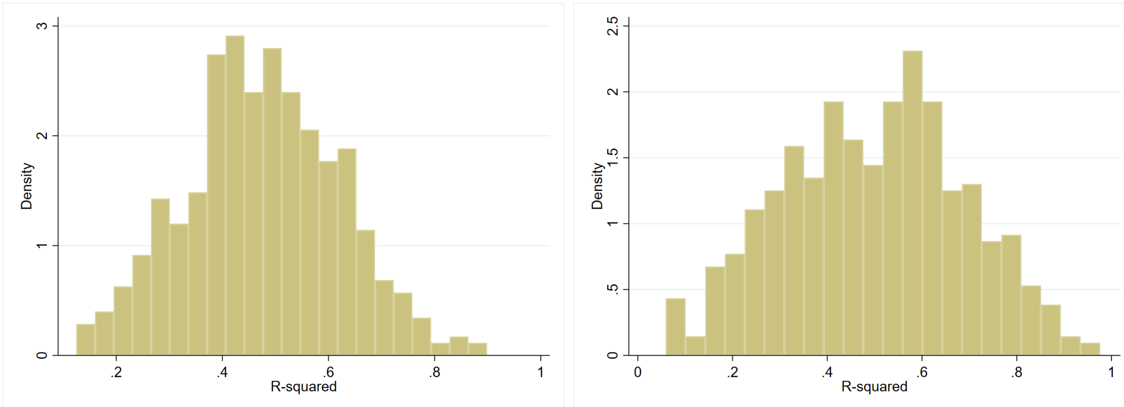
(b) Distance to Urban Center

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.

B.5 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



(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, (4) and (6), across different samples defined by city-period combinations.

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.

$$U_{i,t}^{res} = g(X_i) + \xi + \epsilon_{i,t}^{res} \tag{24}$$

In Eq. (24), $g(x_i)$ captures land i's tendency to be used as residential, and ξ 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:

$$p(X_i, \xi) \equiv \frac{\exp(g(X_i) + \xi)}{1 + \exp(g(X_i) + \xi)} \tag{25}$$

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

$$ID(\xi) = \int_X f(X) \cdot Area(X) \cdot (1 - p(X,\xi)) \cdot IndDisc(X) \cdot dX$$
$$IS(\xi) = \int_X f(X) \cdot Area(X) \cdot (1 - p(X,\xi)) \cdot dX$$

By shifting ξ, the local government can adjust the aggregate land allocation between residential and industrial uses. Imagine now the local government decreases ξ 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 (25) and rearranging, we can find that:

$$\frac{\partial p\left(X,\xi\right)}{\partial \xi} = p\left(X,\xi\right)\left(1 - p\left(X,\xi\right)\right)$$

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

$$Area(X) \cdot p\left(X,\xi\right)\left(1 - p\left(X,\xi\right)\right) \tag{26}$$

Expression (26) states that the marginal industrial land discount loads more on land parcels with higher $p\left(X,\xi\right)\left(1 - p\left(X,\xi\right)\right)$. 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 $p\left(X,\xi\right) = 0.5$, 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 $p\left(X,\xi\right)$ is very close to 1 or 0, the government has a strong preference to sell the parcel as industrial or residential; small changes in ξ will not change the likelihood of selling the parcel as industrial versus residential substantially.

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

Table A.3: 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	1012.83
Logit	1029.34
Nearest neighbor	1037.93

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, which are by aggregating land-level estimates using simple average and weighted by zoning probability predicted by local Logit model and the nearest neighbor model.

pool 2007-2019 together and estimate (β, ξ) 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.3. 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 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.6 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.

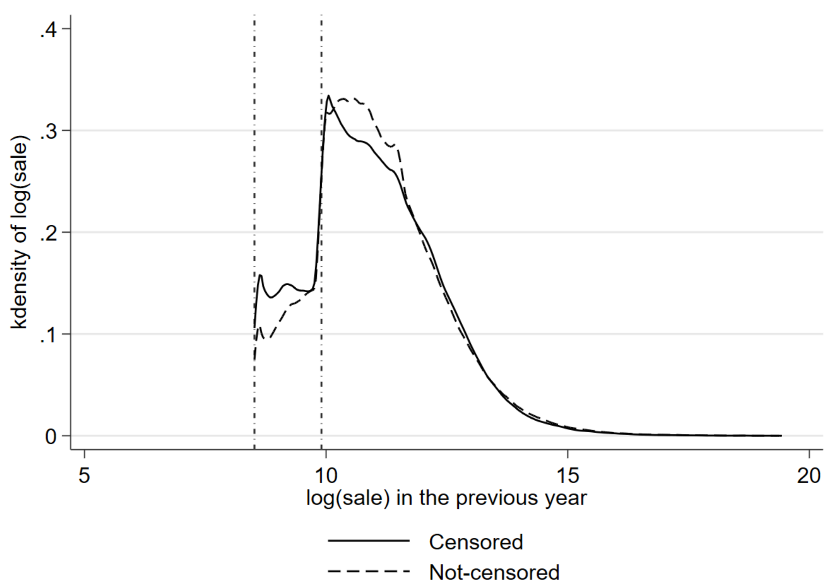


Figure A.4: Distribution of Log(Sale) in the Previous Year

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.

Table A.4: 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.

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 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.4 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' IRR from land sales.

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.

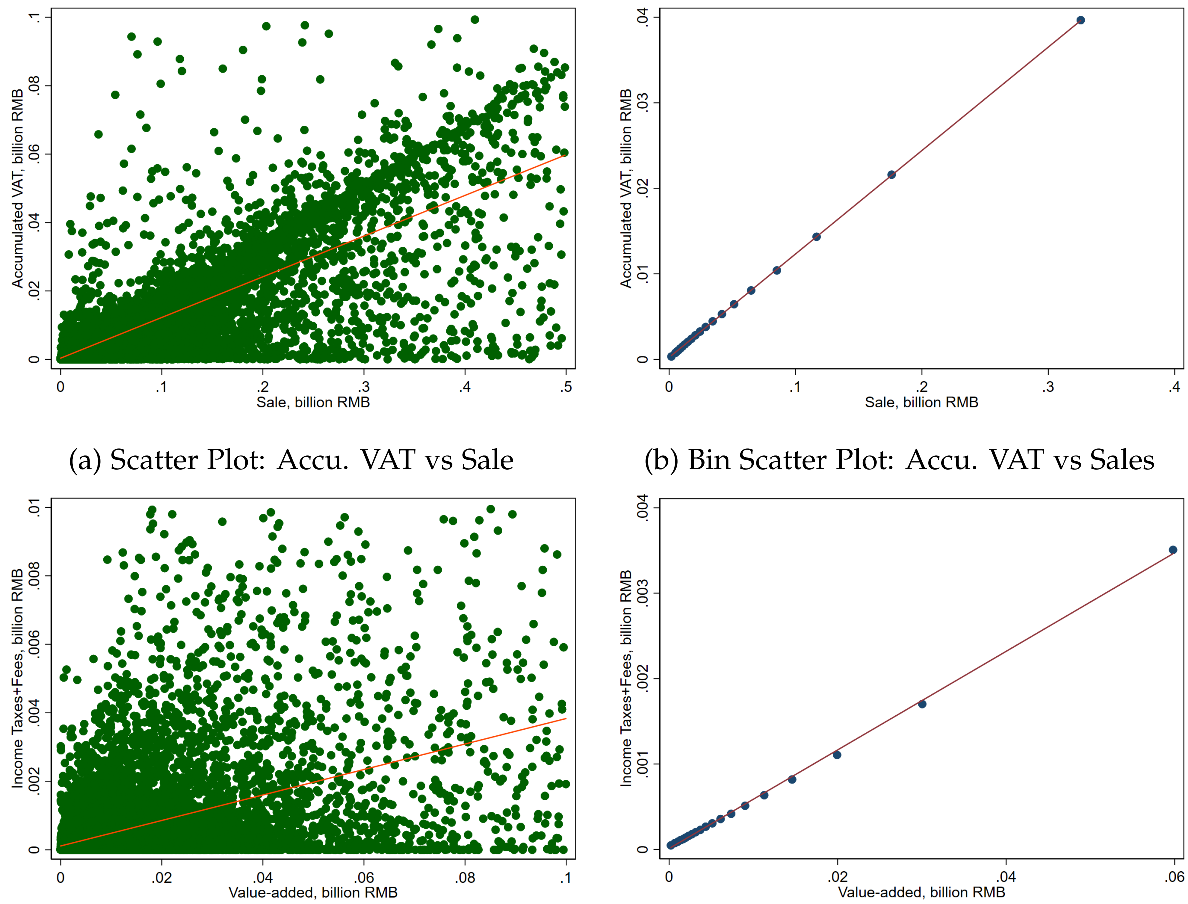
To show that this method produces reasonable results, in Figure A.5, we show a scatterplot and a binned scatterplot of firms' accumulated tax against firms' output. The scatterplot shows that the ratio of accumulated tax to output differs nontrivially across firms: some firms pay a smaller share of output 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 ψ_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 $(12.10\% + 5.77\%) = 17.87\%$



(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.

B.8 Effect of Land Purchases in a Domar Aggregation Model

The foundational theorem of Hulten (1978) states that in a competitive market with a representative consumer, the impact on aggregate TFP of a microeconomic TFP shock is equal to the Domar weight, i.e., the shocked producer's sales as a share of GDP. Hulten's theorem is significant in the sense that sales summarize the macroeconomic impact of microeconomic shocks and we do need to concern ourselves with the details of the underlying production network structures. If we think of the land-purchase as a shock to the producer's TFP, using the same framework as Baqaee and Farhi (2019), we can show that when a firm purchases additional land, the impact on total output in the economy is smaller than the effect on the sales of the land-purchasing firm.

Suppose in each sector of i, there are infinite number of firms indexed by k, and each has its own productivity A_i^k. Building on the framework in Baqaee and Farhi (2019) and using the same notations, the impact of A_i^k on total output is

$$p_c \frac{dY}{dA_i^k} = p_i F_i^k,$$

where p_c is the price of total output Y, p_i is the price of good i, and F_i^k is the production function of firm k in sector i. Now consider the profit-maximization problem of this firm (to simplify the notation we will drop k):

$$\max_{\ell_{i,f}, x_{i,j}} p_i A_i F_i(\ell_{i,1}, ..., \ell_{i,F}, x_{i,1}, ..., x_{i,N}) - \sum_{f=1}^{F} w_f \ell_{i,f} - \sum_{j=1}^{N} p_j x_{i,j},$$

where $x_{i,j}$ are intermediate input of good j used by sector i, and $\ell_{i,f}$ is factor f used by i.

The profit maximization conditions are

$$p_i A_i \frac{\partial F_i}{\partial \ell_{i,f}} = w_f \text{ and } p_i A_i \frac{\partial F_i}{\partial x_{i,j}} = p_j$$

The effect on the firm's sale, $p_i y_i$, is

$$p_i \frac{dy_i}{dA_i} = p_i F_i + \Big(\sum_f w_f \frac{\partial \ell_{i,f}}{\partial A_i} + \sum_j p_j \frac{\partial x_{i,j}}{\partial A_i}\Big) \tag{27}$$

Thus, the increase in firms' sales, (27), will exceed the increase in total output, $p_i F_i$, as long as the difference term is positive:

$$\Big(\sum_f w_f \frac{\partial \ell_{i,f}}{\partial A_i} + \sum_j p_j \frac{\partial x_{i,j}}{\partial A_i}\Big) > 0 \tag{28}$$

The LHS of expression (28) involves the derivatives $\frac{\partial \ell_{i,f}}{\partial A_i}$ and $\frac{\partial x_{i,j}}{\partial A_i}$, which are the changes in inputs induced by the increase in productivity. These will generally be positive: more productive firms will expand inputs. Thus, the increase in sales of the affected firm will be larger than the increase in total output.

The intuition for this result is as follows. When a firm's productivity increases, there is a direct effect on sales from higher productivity and an indirect reallocation effect as the firm changes its purchases of inputs. When the first welfare theorem holds, the reallocation effects do not have a first-order effect on total output, since the marginal inputs are equally productive in all industries. Hence, the sales increase of the affected firm overestimates the increase in total output, whenever the affected firm tends to increase inputs in response to increased productivity.

B.9 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.10 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.

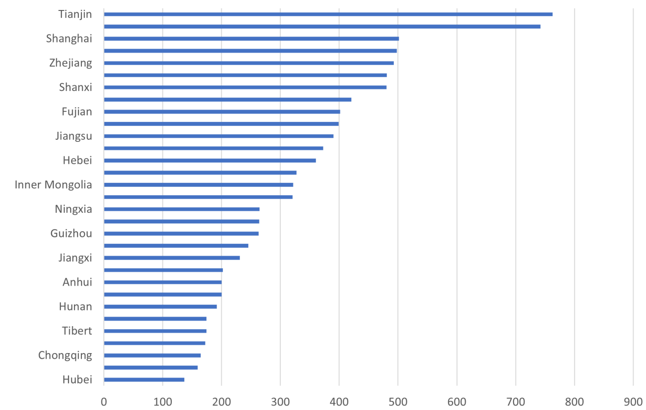
B.11 Classification of Targeted Industries

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.

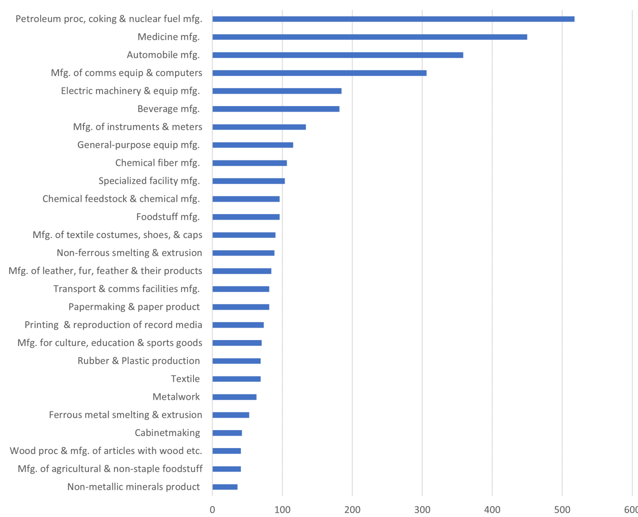
C Supplementary Materials for Section 5

C.1 City Government Industrial Tax Share

In this section, we describe how to get the share of industrial taxes that accrue to the city governments. Manufacturing firms pay three types of taxes and fees: value-added taxes, corporate income taxes, and other taxes and fees. In Section B.7, we estimate that for one RMB increase in firm sales, the value-added taxes increase by 12.10%, corporate income taxes increase by 3.33%, and other taxes and fees increase by 2.44%. The value-added and corporate income taxes are shared with upper levels of governments, and the other taxes and fees all accrue to the city governments. Therefore, the city government share of



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



(b) Requirement on Minimum Tax Payment by Firms on Industrial Land, RMB/m^2

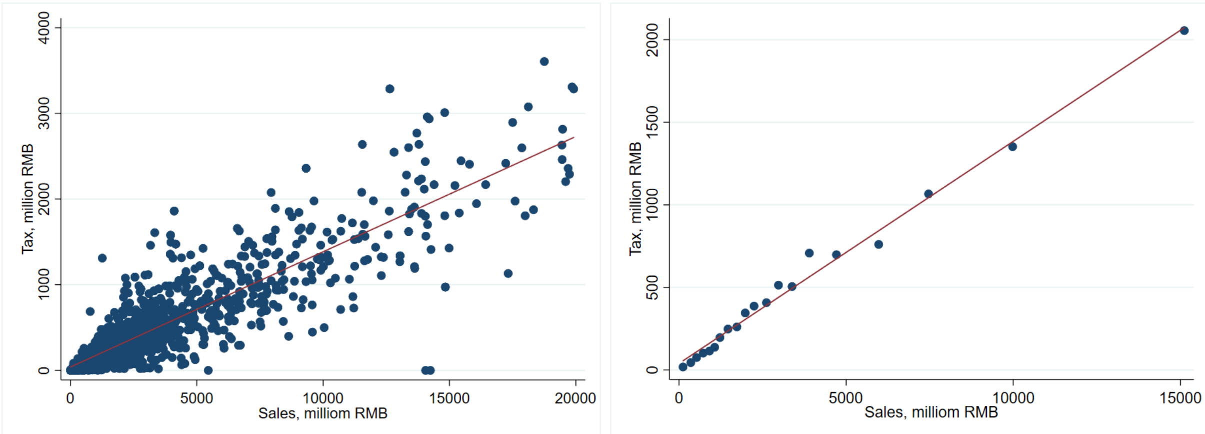
Figure A.6: Supplementary Evidence on Tax Income of Land

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.

industrial taxes is:

$$\mathrm{IndTaxShare}_c = \frac{12.10\% \times \mathrm{VATShare}_c + 3.33\% \times \mathrm{ITShare}_c + 2.44\%}{12.10\% + 3.33\% + 2.44\%} \tag{29}$$

To aggregate $\mathrm{IndTaxShare}_c$ to the national level in a way comparable to the estimation of IRR during 2007-2010, we calculate the average $\mathrm{IndTaxShare}_c$ weighted by the size of land purchased by firms during 2007-2010 used in the estimation in Table 3 Column (1), just as we aggregate the industrial discounts and developer taxes. The weighted-average $\mathrm{IndTaxShare}_c$ turns out to be 31.66%.



(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.

C.2 City Govt Developer Taxes

As our primary interest is in the industrial land discounts, we examine the causal effect of city government discount rates and the share of tax revenues on the industrial land discounts in Section 5. However, the theoretical framework links the present value of industrial tax cash flows with the upfront industrial discount plus the developer taxes. In this section, we complete the analysis by looking at the developer taxes. We start by calculating the amount of developer tax revenues that accrue to the city governments, and then show the causal effect of local government discount rates and tax shares separately.

C.2.1 City Government's Developer Tax Rate

In this section we describe how we calculate the developer's tax rate $DevTaxRate_{ct}$, that belongs to the city governments c in year t.

Before May 1, 2016, home developers pay income taxes (IT), business taxes (BT) and various other kinds of taxes and fees. The city governments share the income taxes and business taxes with upper level of governments and keep the entirety of other taxes and fees. In the data of listed developers, we observe three related variables: sale, income tax, and business tax and surcharges (BTS). The last variable, BTS, includes business taxes and other taxes and fees. The BT is set to be 5% of total sales. We then calculate the city's developer tax rate as follows:

$$CityDevTaxRate_{c,t} = \mathbf{E}_t[\frac{d\ IT_{i,t}}{d\ Sales_{i,t}}] \times ITShare_{c,t} + \mathbf{E}_t[\frac{d\ BTS_{i,t}}{d\ Sales_{i,t}}] - 5\% + 5\% \times BTShare_{c,t}$$

After May 1, 2016, the BT is replaced with VAT, and BTS is replaced with TS which only includes other taxes and fees. We do not observe VAT in the income statements because it is not regarded as the firms' costs. We estimate it with (Sales - COGS) times the VAT rate. We calculate the city's developer tax rate as follows:

$$\begin{aligned} CityDevTaxRate_{c,t} = & \mathbf{E}_t[\frac{d\ IT_{i,t}}{d\ Sales_{i,t}}] \times ITShare_{c,t} + \mathbf{E}_t[\frac{d\ TS_{i,t}}{d\ Sales_{i,t}}] + \\ & \mathbf{E}_t[\frac{d\ (Sales_{i,t} - COGS_{i,t}) \times VATRate_t}{d\ Sales_{i,t}}] \times VATShare_{c,t} \end{aligned}$$

For $t = 2016$, as the BT was in place for 1/3 of the year and VAT for the rest 2/3, we use a weighted average rate, 1/3 times the rate in 2015 plus 2/3 times the rate in 2017.

We can now calculate $CityDevTax_{c,t}$, the amount of developer taxes that accrue to

Table A.6: Developer Taxes and Municipal Corporate Bond Yield

Specification	OLS	OLS	IV	IV
Dep Var: DevTax	(1)	(2)	(3)	(4)
CMCBYield, %	-395.1***	-257.0***	-1,183***	-1,490***
	(-6.778)	(-6.216)	(-6.093)	(-2.737)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,222	1,222	1,222	1,222
R-squared	0.360	0.499	-0.766	-1.548
#City	238	238	238	238
F statistic			25.13	6.050

Note: This table shows the regression of cities' home developer taxes on City MCB yields, i.e., the average yields of MCBs weighted by the bond size. The first two columns report the OLS estimation results and the last two columns report the 2SLS estimation results where the City MCB yield is instrumented by $\mathsf{LateTerm}_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the city governments, as follows:

$$\mathsf{CityDevTax}_{c,t} = P^h_{c,t} \times \mathsf{FloorRatio}_c \times \mathsf{CityDevTaxRate}_{c,t}$$

C.2.2 Tax Incentives and Developer Taxes

With the same specification as Eq. (19), we replace the dependent variable with the city's developer taxes $\mathsf{CityDevTax}_{ct}$. The result is shown in Table A.6. A higher city government discount rate affects the city's land allocation decisions, leading to not only a lower industrial discount but also lower city developer tax revenues as a result of lower house prices. The negative effect holds for both the OLS specification and the IV regressions, regardless of the inclusion of other city controls.

With the same specification as Eq. (20), we then use developer taxes as the dependent variable. As shown in Table A.7, we find that cities with higher increase of VAT share experienced larger increase in developer taxes per square meter after 2016. This is because house prices increased in areas with larger increases in city governments' VAT shares, leading city governments' tax revenues from developers to also increase in these areas.

Table A.7: City VAT Share and Develoer Taxes

Dep Var:		DevTax	HousePrice
		(1)	(2)
$\Delta VATShare\times$			
Year=	2012	-1.844	-32.10
		(-0.382)	(-0.465)
	2013	0.674	-31.28
		(0.165)	(-0.518)
	2014	-5.142	-79.06
		(-1.372)	(-1.321)
	2016	2.495	-10.13
		(0.590)	(-0.175)
	2017	9.535	87.19
		(1.631)	(1.544)
	2018	25.34***	187.1***
		(3.053)	(2.865)
	2019	6.936	200.6***
		(1.221)	(3.120)
Year FE		Yes	Yes
City FE		Yes	Yes
Observations		1,877	1,885
R-squared		0.900	0.901
#City		246	247

Note: This table shows how the change of the city VAT share affects the city's developer taxes. The sample includes all the municipal cities for which we have the $DevTax_{c,t}$ estimates from 2012-2019, and the year 2015 is used as the baseline. The treatment variable, $\Delta VATShare$, is of unit %. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C.3 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 (20), 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 government. 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.8: 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.[42] 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.

Table A.8: 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

[42]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.