Industrial Land Discount in China: A Public Finance Perspective*

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Abstract

China's land market features a substantial *industrial discount*: industrial-zoned land is an order of magnitude cheaper than residential land. In contrast to explanations centered on subsidies to industry or promoting industry growth, we emphasize the importance of future tax revenues from the land and find that local public finance incentives can largely rationalize this price gap. Under the "land finance" system, land sales are an important source of revenues for Chinese local governments. We show that local governments, who serve as monopolistic land sellers in China, face a trade-off between supplying residential or industrial land that is determined by the different time profiles of revenues from industrial and residential land sales, local governments' financial constraints, and the extent of local governments' tax revenue sharing with other levels of government.

Keywords: Land allocation, Municipal corporate bonds, Housing market, Discount rate

JEL classifications: H70, G31, R14, R38

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1 Introduction

China's land market is perhaps one of the key drivers of the extraordinary growth of the Chinese economy in the past forty years. One of the unique features of China's land market is the practice of "land finance" (Lin and Yi, 2011; Liu et al., 2014) by which local governments, who serve as monopolistic sellers in the local land market, heavily rely on land sales for fiscal revenue (see, e.g., Liu and Xiong, 2020). This differs drastically from other developed economies where municipal governments finance a significant part of their public expenditure via the residential property taxes (Ahern, 2021), which is absent in China.

Just like in many other countries, there are rigid zoning restrictions in China. As highlighted in Chen et al. (2018), land zoned for residential use sells at roughly a ten-fold higher price than land zoned for industrial use. In 2019 the average price of residential land in China was 3,619 RMB/m^2, while the average price of industrial land was 304 RMB/m^2. We call this price difference between residential and industrial land the *industrial land discount* (or *industrial discount* interchangeably). Our paper aims to offer a comprehensive study of this industrial discount, which has profound implications for the real estate market, public finance, economic growth, and even political economy in China.

The typical view in the literature is that residential land sales are primarily a way for local governments to raise revenues, whereas industrial land is sold primarily to subsidize industry, stimulate economic growth, and support labor demand. In support of this view, Liu and Xiong (2020, pp. 193) state that "it is common practice for local governments throughout China to offer industrial land at subsidized prices to support local industries."[1]

This paper proposes an explanation for the industrial discount that stems from local public finance rather than from subsidies to industry. We propose that the choice between residential and industrial land sales involves an intertemporal revenue tradeoff. Chinese local governments are predominately funded through a combination of corporate tax revenues and land sale revenues; in 2019, these

[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.

two numbers were roughly 8.7 trillion RMB and 7.3 trillion RMB respectively.[2] Industrial land generates persistent tax flows, since industrial firms pay value-added taxes, income taxes and various fees. Since there are no residential property taxes in China, residential land sales create only a temporary increase in taxes paid by home developers. [3] This implies that local governments face a choice between selling residential land with larger upfront revenues and selling industrial land which pays more persistent cash flows of tax revenues over time.

This dynamic perspective implies that the large upfront industrial land discount does not necessarily imply that governments are systematically subsidizing industry through cheap land. Indeed, we show that the flow of tax revenues from industrial land, after adjusting for taxes paid by residential developers, can quantitatively compensate for the upfront industrial land discount. We also provide causal evidence that local governments' financing needs affect land zoning, suggesting that local public finance plays an underappreciated role in shaping the path of China's economic growth through the land allocation channel.

We start with a framework to analyze the forces that drive the equilibrium return from supplying industrial rather than residential land. Assume the local government's objective is to maximize the present value of its fiscal revenues. Besides the upfront land sale revenues that all belong to the local government, residential land generates a one-time tax paid by home developers, while industrial land generates a persistent cash flow of tax revenues, which is shared with the central government. In equilibrium, the local government sells industrial land at a lower price due to the future tax benefits. The framework points to two measurable summary statistics. The first is the industrial discount, i.e., the price difference between industrial and residential land. The second is the internal rate of return (IRR) on industrial land sales, i.e., the discount rate which equates the present values of all cash flows from industrial and residential land sales.

The model makes two predictions about industrial discounts. The first concerns governments' cost of capital: when local governments are less patient, they will sell more residential land, depressing residential prices and thus industrial discounts.

[2]For detailed calculation, see the last paragraph in Section 2.1.

[3]As of February 2022, there is no nationwide property tax on residential properties in China. The formal introduction of a property tax was put on the policy agenda in October 2021, though whether and how to implement a property tax remain the most debated policy in recent China.

The second concerns the fraction of industrial tax revenues which accrue to local governments: if local governments capture more of the tax revenues from industrial land sales, they will sell more industrial land, increasing industrial discounts.

Taking this framework to the data requires three datasets. The first is data on the universe of land parcels sold by the government from 2007 to 2019. We observe the price of each parcel, the name of the buyer, the land zoning, and characteristics of the parcel such as its location and size. The second is 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 firm who acquired each land parcel during 2007-2010, for which we can estimate the consequent effect of land purchase 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.

To show the quantitative importance of future tax revenues as compared to industrial discounts, we first calculate the IRR on industrial land sales, which requires estimation of three quantities: the average discount on industrial land versus residential land; the long-term increase in tax revenues from firms who purchase industrial land; and the one-time tax revenues paid by home developers when they sell housing units. We emphasize that all inputs are based on their respective sample periods and do not suffer from the usual "look-ahead" bias.

We first estimate the industrial discount based on a potential-outcomes framework. We use observed residential (industrial) sale prices to estimate a hedonic model to predict what the prices of industrial (residential) land parcels would have been if they were, counter-factually, sold as residential (industrial). We then estimate the industrial land discount by taking the difference between the actual (predicted) residential price and the predicted (actual) industrial price. During 2007-2010, the average industrial land discount is estimated to be 1012.83 RMB/m^2.

Next, to estimate the marginal tax revenues from industrial land sales, we first use a differences-in-differences approach to estimate the marginal impact of land purchases on firms' sales. We then estimate marginal tax revenues by multiplying the increase in sales by an effective tax rate, taking into account the spillover effect on, in particular, the upstream firms. For land purchase during 2007-2010 and using firm sales and tax data until 2013, the average annual future marginal taxes are 113.6 RMB/m^2 in the first three years, and 214.2 RMB/m^2 thereafter.

Finally, we estimate the incremental tax revenues paid by home developers. For simplicity, we assume the developer taxes occur only once and accrue in the next year after land acquisition. We find that for residential land sold during 2007-2010, the average developer tax in the next year is about 1453.03 RMB/m^2.

These estimates allow us to back out the IRR implied by the industrial-residential land tradeoff. We find that during 2007-2010 the industrial land IRR, i.e., the discount rate that equates the present value of industrial versus residential land sales, is 7.70%. The estimated IRR is comparable to, but at the high end of, local governments' cost of capital, which when proxied by their bond yields ranges between 3.5% and 7.5%. Thus, industrial land sales in China are not subsidized relative to residential land sales, once we take future tax revenues into account. This is the main takeaway of our paper.

We take our methodology to further estimate the industrial IRR over time, with more recent industrial land discounts and home developer tax data but holding the industrial taxes 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 discount is roughly 3.80%, which is smaller than usual estimates of the government discount rate. Under our framework, the decreasing trend can be explained by the increasing share of tax revenues that accrue to local governments, especially the 2016 tax reform that doubled the local governments' share of value-added taxes.

Based on these findings, we propose that land allocation decisions in China are essentially determined by the interaction of three forces: the "land finance" system, through which land sales are a core source of local governments' operational revenues; the distinct time profiles of revenues from industrial and residential land sales along with the governments' financial constraints; and the way that tax revenues are split between the central government and local governments. The last two points are new to the literature on industrial discounts, and Section 5 provides further evidence that industrial discounts are associated with local governments' discount rates as well as local governments' share of industrial tax revenues.

First, if local governments' choice between industrial and residential land sales represents an intertemporal revenue tradeoff, industrial discounts should be lower when the governments' discount rates are higher, e.g., when the governments are less patient or face greater financial constraints. Consistent with this hypothesis, 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 for municipal corporate bond yields using an instrument that builds on Chen et al. (2020). Second, we show that industrial land discounts are positively correlated with city governments' shares of value-added taxes in the cross-section. Exploiting a 2016 change in local-central tax sharing, we show that cities that experienced a larger increase in their share of value-added taxes subsequently exhibited greater increases in their industrial discounts.

Literature Review. Our paper relates to the following strands of literature. Many papers have argued that local governments in China tend to suppress industrial land prices while inflating residential prices to support local industries. Liu and Xiong (2020) show the diverging trends between industrial, commercial, and residential land prices, and argue that the industrial price gap is due to local governments' incentives to subsidize local industries. Tao et al. (2010) empirically document that Chinese local governments used subsidized industrial land in competition for investment, with prefecture-level data between 1995 and 2003. Also using prefecture-level data but from 2003 to 2012, Lei and Gong (2014) argue that, in order to increase fiscal income and city output, it is optimal for local governments to distort the relative prices of industrial and residential lands, due to the agglomeration effects of industrial land sales and future tax revenues from firms. Fan et al. (2015) model Chinese local governments' incentive to increase the industrial land supply to generate more labor inflow and faster urbanization. While we may refute some explanations, our perspective is largely complementary to these alternative views.

Researchers have also related various local government incentives to land market distortions. Xie et al. (2019) test the effects of VAT sharing and business tax sharing on local governments' land allocation decisions. Tian et al. (2022) match land transaction data with industry-county-specific characteristics, and show that industries which generate stronger spillover effects to local incumbents through agglomeration were favored in land allocation by governments.

There are several papers that empirically investigate price distortions in the Chinese land market due to corruption. Cai et al. (2013a) and Li (2019) show that the local governments take advantage of differences between auction formats to influence effective land prices. Chen and Kung (2019) argue that firms with links to Chinese political elites are able to obtain large price discounts in the land market.

Relatively little research directly examines the return on land sales. One exception is Fu et al. (2021), who calculate the average productivity of land using city-level data and show that a growing share of the land conversion (from agriculture to urban) quota is allocated to less productive cities. A few researchers study the quantitative implications of land market distortions. Deng et al. (2020) infer housing and land market frictions from data on housing and land investment and sales, and study the quantitative impact of those frictions.

This paper proceeds as follows. Section 2 describes institutional details of the Chinese land market and our data. Section 3 introduces a conceptual framework illustrating the local governments' tradeoff between industrial and residential land sales. Section 4 shows how we estimate industrial discounts, marginal tax revenues generated by industrial and residential land sales, and government IRRs. In Section 5, we show how industrial discounts are associated with local governments' cost of borrowing and shares of industrial tax revenues. We conclude in Section 6.

2 Institutional Details and Data

2.1 Institutional Background

The Chinese land market. There was no formal land market in China before the 1980s. The development of market-based "commodity housing" in the 1990s opened up land leases for the residential market. The industrial land market was also developed together with the reform of state owned enterprises and the growth of private firms. The 1994 Tax-Sharing Reform made land lease sales an important source of local government revenue, spurring the take-off of the Chinese land market. However, regulations for the land market were not fully in place yet; without any requirement to release land lease contracts to the public, local governments had a great deal of leeway in granting land leases via hidden "negotiations." Combined with the substantial ambiguities in the scope of property rights at that time, land leases were often granted significantly below market values, leading to corruption and efficiency losses (Cai et al., 2013a).

During the late 1990s and early 2000s, Beijing passed several laws and regulations to formalize the land market, with the intention of banning private negotiated deals from the local government. Most land leases were required to be sold at market prices, through a variety of different market mechanisms. Auctions are the most favored mechanism, during which most of the information about the land, as well as details about the pricing process, are revealed to the public. Governments are also allowed to use "agreements" to set prices, if the requirements for auction are not met. Regardless of the sale method, local governments have been required to make deeds records publicly available since 2004. The permitted uses for each land parcel—analogous to zoning restrictions—are also strictly regulated. There are four land use categories: residential, industrial, commercial, and public utility.

Land quota system and land allocation. The Chinese government imposes a land quota system that plans out the maximum amount of newly developed urban land for each city over different horizons. The quota system is first "top-down." It is based on land use master plans (usually covering 15 years) from the national level down to the city level. At higher levels of government, these plans are jointly carved out by several national ministries and the provincial governments. The system is also "bottom-up." At the lower level, city governments participate in drafting those plans and provide feedback to higher level governments. Besides the long-term land use master plan, there are also five-year land use plans drafted by city governments and then reviewed and approved by the provincial and national government. In addition, the master plan generally gets modified or amended every five years, reflecting input from all levels of government.[4]

Under the total quotas set by these medium- and long-term plans, local governments decide how to implement these land supply plans in the short-run. Each year, based on its economic development needs, a local government first decides how much quota they will need out of their medium-long-term cap, then files a proposal with the Ministry of Natural Resources, and finally supplies land according to the quota after approval. Importantly, the quota issued by the Ministry of

[4]In addition, sometimes off-schedule modifications are possible, for example when higher-level governments see issues in the land market, or when a local government files an application for a change of land usage plan.

Natural Resources concerns only the total area of land supplied across all uses, so local governments have freedom in allocating the quota to different types of land. The Ministry of Housing and Urban-Rural Development publishes guidelines on the split of different types of land usage in a city. For example, the 2012 Code states that residential land share should fall between 25% to 40% and the industrial land share between 15% to 30%.[5] However, these guidelines are generally loosely stated and not necessarily binding. Overall, local governments tend to have substantial control over land supply composition in the short run.

Land allocation and local government financing. Land allocation has important implications for Chinese local government public finance. As highlighted by a team of named Chinese scholars and policy makers (Cai et al., 2013b), "Land finance is a key challenge: most Chinese cities fund their urban infrastructure largely from land sales; 40% of the government debt needs land finance in 2010; land sale revenue accounts for about one third of total local government revenue during 2010-2012." Another important role played by land is that future land reserves can serve as collateral for local government debt; according to a report from the Chinese National Audit Office, 37.23% of local government debt explicitly pledged future land sales revenue as collateral by the end of 2012.

Tax revenues from firms also play an important role in funding local governments in China. According to the Ministry of Finance, local governments' total fiscal revenue in 2019 largely comes from three sources: 10 trillion RMB from general revenue, 7.5 trillion RMB from the central government transfer payments, and 8 trillion RMB from local government-managed funds (7.3 trillion RMB from land sales).[6] Since about half of the local government general revenues and central government transfers are from value-added taxes and corporate income taxes, local government revenue from the two tax items is about 8.7 trillion RMB ($\approx \frac{10+7.5}{2}$). The overall picture is that, as the top two sources of revenue, taxes from firms and direct land sales together cover over 60% of local government's budget in China.

[5] See the 2012 Code for classification of urban and rural land use and planning standards for development land. These codes are routinely updated.

[6] See the Ministry of Finance's 2019 Report on the execution of the central and local budgets.

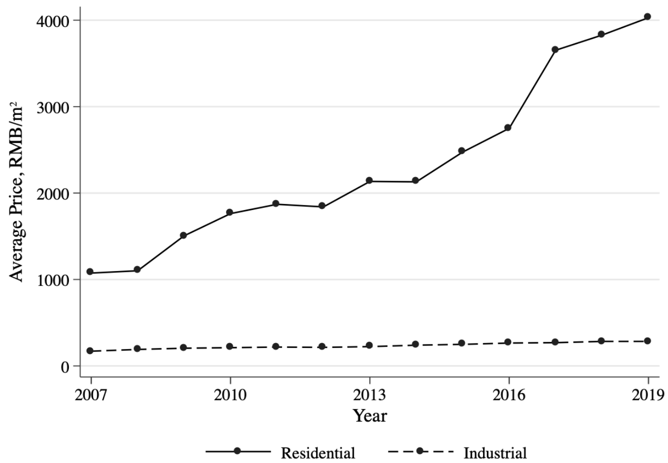


Figure 1: Average Land Prices Over Time by Land Use: Industrial vs. Residential

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.

2.2 Data

Land sale data. We use land sale data from the Ministry of Natural Resources. This dataset covers the universe of land sales by the local governments in China from 2007 to 2019. We focus on residential and industrial land parcels allocated by agreement, tender, auction and listing.[7] 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 all the latter three allocation methods. We retrieve data on the geographical coordinates of land parcels using the Gaode maps API, a leading Location Based Services (LBS) provider in China.[8] We define markets as urban units, which are contiguous urban clusters as identified by satellite images (see Appendix A.2). 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.

Firm data. To estimate the tax yield on the industrial land, we take industrial firm data from the National Survey of Industrial Firms (NSIF), which is collected by the

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

[8]See https://lbs.amap.com/.

National Bureau of Statistics on all industrial (manufacturing, mining, and utility) firms in China during 1998-2013. Despite some concerns about the data quality (Nie et al., 2012), the data has been widely used in economic research on China.[9] Besides the issue of missing 2010 data,[10] it is also subject to censoring and random dropout concerns, which we analyze in appendices A.1 and C.2.

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, while the control firms are those who never purchased any new land during this period.

In total, we are able to merge 22,636 transactions out of a total of 124,341 industrial land purchases by firms via agreement, tender, auction and listing during 2007-2010. In the NSIF 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 land parcels and firms to the universe of parcels and firms. Merged parcels are slightly more expensive, and 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 covers all the municipal cities in China during 2007-2018.

[9]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).

[10]For the year 2010, all operating information except sales and employment is missing, and we drop that year due to concerns about data quality.

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	9275.224	28673.8	443.5946	2352.02	18326.41
Cost, million RMB	1,729	6328.855	20170.43	281.86	1450.66	12380.3
OtherTax, million RMB	1,729	737.2629	2203.758	10.1488	189.44	1453.62
IncomeTax, million RMB	1,729	432.1878	1406.951	5.802	115.9482	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.

3 Conceptual Framework

We start with defining the industrial land discount, followed by a conceptual framework that highlights the intertemporal revenue tradeoff faced by local governments under the Chinese fiscal system.

3.1 Industrial Land Discounts

The core object of our study is the discount of industrial land relative to residential land. A striking pattern shown in Figure 1 is: industrial land prices are an order of magnitude lower than residential land prices throughout our sample period. Given that a large share of local government revenue derives from land sales, this raises the question of why a revenue-maximizing local government did not reallocate land from industrial to residential uses until the prices in the two markets equalize.

Consider a single parcel of land to be sold in period t, and let p_t^{ind} and p_t^{res} denote the parcel's expected price per square meter, if it is sold as industrial or residential land. As we are interested in governments' net revenue from selling lands, we need to adjust both p_t^{ind} and p_t^{res} for their respective costs. In general, there are three kinds of costs for land sales, some of which differ between industrial and residential lands. First, there is a fixed component, which mainly includes the "standard" compensation to incumbent land occupants and the cost of land development. These fixed costs apply equally to both types of land and cancel out when calculating the industrial discount. The second type of cost is the "non-standard" compensation to local land occupants, which depends on the expected land sale price. Typically, incumbent occupants know whether the redeveloped land is intended for residential or industrial uses. Rent-sharing with incumbents is a large part of the costs of residential land sales, but matters little for industrial land sales—generally, industrial land sales generate relatively negligible upfront revenues and thus involve less negotiation with local occupants. Third, as laid out in the Code for Planning Standards (see footnote 5 Item 4.3.2), selling residential land involves certain auxiliary costs, including extra land and fiscal support for education and other services associated with new residences. The latter two variable costs only apply to residential land, and in Appendix C.1 we estimate that the sum of these two variable costs is about 1/3 of residential sale revenues.

Denote the additional cost associated with residential land by $\lambda = 1/3$. Throughout the paper we define the industrial land discount as:

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

Note that the extra cost imposed on residential land could explain part of the price differences observed in Figure 1. As shown shortly in Section 4, however, auxiliary costs alone are too small to explain the entirety of the price differences.

3.2 Tax Revenues and the IRR on Industrial Land Sales

As explained in the introduction, one factor in the choice between allocating a new land parcel for residential versus industrial purposes is the distinct time profiles of revenues from industrial and residential land sales. In this section we first formally define IRR^{ind}, the internal rate of return (IRR) on industrial land sales. We then develop a simple framework to link IRR^{ind} to the local government's discount rate, its tax sharing rule with higher governments, and demand elasticities in the two land markets.

3.2.1 IRR on Industrial Land

Following the terminology in practice in corporate finance (Berk and DeMarzo, 2017), we define the IRR on industrial land as the discount rate ρ that equates the net present value of industrial versus residential land sales:

$$\underbrace{\sum_{s \geqslant t+1} \frac{\mathrm{Tax}_{t,s}^{ind}}{(1+\rho)^{s-t}}}_{\mathrm{PV}(\mathrm{tax}^{ind})} - \underbrace{\sum_{s \geqslant t+1} \frac{\mathrm{Tax}_{t,s}^{res}}{(1+\rho)^{s-t}}}_{\mathrm{PV}(\mathrm{tax}^{res})} = \underbrace{(1-\lambda)p_t^{res} - p_t^{ind}}_{\mathrm{IndDisc}} \tag{2}$$

In Eq. (2), the right hand side is industrial land discount as defined in Eq. (1). On the left hand side, $\mathrm{Tax}_{t,s}^{ind}$ is industrial taxes per square meter of land in year s due to firms' land purchase in year t, and $\mathrm{Tax}_{t,s}^{res}$ is residential taxes per square meter of land in year s due to home developers' land purchase in year t. We invoke the convention that tax cash flows start to accrue one year after the land purchase.

Unlike the industrial taxes that occur every year after t, the residential tax revenues are temporary and we need to take a stance on their timing. In practice, some taxes, such as the deed taxes and stamp tax, are paid at the time of land acquisition; others, such as the value-added and income taxes, will be paid when the houses are "advance sold," which generally occurs within three years after the land acquisition. For simplicity, we assume all the residential taxes occur in the next year following the land acquisition. That is to say, we assume that $\mathrm{Tax}_{t,s}^{res} = \mathbf{1}_{s=t+1} \times \mathrm{DevTax}_s$ with DevTax_s denoting the developer taxes per square meter of residential land in year s.[11]

In summary, we define IRR on industrial land sales, IRR^{ind}, to be

$$\mathrm{IRR}_t^{ind} \equiv \left\{ \rho : \underbrace{\sum_{s \geqslant t+1} \frac{\mathrm{Tax}_{t,s}^{ind}}{(1+\rho)^{s-t}}}_{\mathrm{PV}(\mathrm{tax}^{ind})} = \underbrace{(1-\lambda)p_t^{res} - p_t^{ind}}_{\mathrm{IndDisc}} + \underbrace{\frac{\mathrm{DevTax}_{t+1}}{1+\rho}}_{\mathrm{PV}(\mathrm{DevTax})} \right\} \tag{3}$$

Eq. (3) allows us to calculate IRR_t^{ind} after we obtain estimates for all inputs (industrial discounts, Tax^{ind}, and DevTax) in Section 4.

3.2.2 Equilibrium IRR^{ind} from the Government Optimization Problem

Under the premise that land allocation decisions made by Chinese local governments reflect the intertemporal tradeoff outlined above, what should be the relation between IRR^{ind} and the government's cost of capital, denoted as r^{gov}? In a frictionless benchmark where the government lacks monopoly power and internalizes all tax revenues fully, its indifference condition between selling a marginal land parcel as industrial versus residential indeed implies that $\mathrm{IRR}^{ind} = r^{gov}$. There are, however, a number of economic and/or policy factors that could drive a wedge between IRR^{ind} and r^{gov}.

First, city governments keep almost the entirety of their land sales revenue, but only a fraction of taxes paid by local firms. The value-added, corporate income and business taxes are all shared between the city and upper-level governments. In Section C.8 of the appendix we report the effective share of all industrial taxes that accrued to city-level governments during 2007-2010 to be 31.66%. Suppose that the city government only internalizes a share $k \in (0, 1)$ of tax revenues

[11] In Section 4.4.2 we consider the alternative case that DevTax occurs two years later and show that our results are robust to this choice.

from industrial firms. If we think of city governments as fully determining land allocation decisions and they only care about the revenues they get, k can be thought of as the share of taxes that accrue to city governments. More realistically, city governments negotiate with higher-level governments over land allocation decisions; k can then be thought of as the eventual weight that the bargaining outcome places on tax revenue in determining land allocations.

In Appendix B, we construct a stylized model with perpetuity cash flows. When city governments only internalize k future tax revenues, we will have:

$$\mathrm{IRR}^{ind} = \frac{r^{gov}}{k}. \tag{4}$$

Intuitively, the smaller the share of future industrial taxes that a city government receives, the greater the required industrial tax revenues in order for the government's indifference condition to hold, and hence the higher IRR^{ind} will be. As $k < 1$, $\mathrm{IRR}^{ind} > r^{gov}$.

Second, since Chinese local governments are monopolistic sellers in their local land markets, the marginal revenue may differ from price. Taking the simple model developed above but further incorporating different demand elasticities in industrial and residential land markets, in Appendix B we show that

$$\mathrm{IRR}^{ind} = \frac{r^{gov}}{k} \times \left[1 - \frac{\overbrace{\sigma_{res}^{-1} - \sigma_{ind}^{-1}}^{\text{wedge in inverse semi-elasticities}}}{\text{IndDisc + DevTax}} \right], \tag{5}$$

where σ_{res} (σ_{ind}) is the negative demand semi-elasticity of residential (industrial) land.[12] The demand elasticity for industrial land is likely to be greater than that for residential land, as firms typically shop around among different cities while most households do not move across cities.[13] We therefore would expect the term in brackets in Eq. (5) to be less than 1. Intuitively, the monopolistic local government takes into account the price impact it has in the residential land market and tends to maintain a higher industrial land discount, generating a lower implied IRR^{ind}.

[12]In this derivation, for exposition purposes we further assume that the one-time developer taxes $DevTax$ occur at the same time as the sale of residential land.

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

As a result, the relationship between IRR^{ind} and r^{gov} is ambiguous, depending on the relative size of k and the term in brackets. In Section 4.4.3 we show IRR^{ind} goes from larger to smaller than r^{gov} during 2007-2019, likely driven by the increase in k during that time period.

Before we move on to the next section to estimate IRR^{ind} formally, we stress that IRR^{ind} in Eq. (3) incorporates the industrial firms' marginal tax revenues only; it ignores potential non-pecuniary benefits or costs that the government derives from choosing industrial rather than residential zoning. One advantage of our approach, which provides a gauge of the magnitude of IRR^{ind}, is that it gives a clear guidance on whether one particular economic force alone, i.e., taxes, can explain the striking empirical pattern.

4 Estimation

In the framework laid out in Section 3, measuring industrial land discounts and estimating government IRRs requires three key quantities: p_t^{ind} and 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 $DevTax_s$, the taxes paid by home developers in year s based on home developing business on the residential land. We provide these estimates in this section. After estimating industrial discounts in Section 4.1, we use a differences-in-differences approach in Section 4.2 to estimate the marginal effect of land purchases on industrial firms' sales and taxes. Section 4.3 conducts the estimation of taxes paid by developers. We then combine these estimates to calculate IRRs on industrial land sales in Section 4.4.

4.1 Industrial Land 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 parcel assuming it is sold as residential (industrial) land. Let $\mathbf{1}_{it}^{res}$ be a dummy representing whether parcel i is actually sold as a residential parcel. The sale price for parcel i that we observe is:

$$p_{i,t} = p_{i,t}^{res} \times \mathbf{1}_{i,t}^{res} + p_{i,t}^{ind} \times (1 - \mathbf{1}_{i,t}^{res}) \tag{6}$$

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 the city center are more likely to be used as residential as opposed to industrial. Therefore, one cannot directly take the average observed prices of residential land parcels as the predicted price of the industrial land parcels, if they were instead zoned for residential use. We must control for the differences in land characteristics between the two types of land parcels.

We proceed by using the sample of observed residential (industrial) sale prices to estimate a hedonic model to predict what the prices of industrial (residential) land parcels would have been if they were, counter-factually, 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:

$$p_{i,t} = X_{i,t} \cdot \beta^{res} + \gamma_{u,t}^{res} + \epsilon_{i,t}, \ \forall i \in \mathcal{I}_{res}. \tag{7}$$

Eq. (7) is a hedonic model that predicts $p_{i,t}$, the price per square meter of each residential land parcel. To control for geographical variation in prices within cities, we construct "urban units," which are geographical units smaller than cities, by grouping contiguous pieces of urban land into blocks. We include urban-unit-by-year fixed effects $\gamma_{u,t}^{res}$.[14] Parcel characteristics $X_{i,t}$ consist of the following control variables: second-order polynomials in the log area of the land parcel, the distance to the closest urban unit center, and the year-quarter in which the land is sold.

We estimate Eq. (7) by restricting the sample to the set of land parcels sold by auctions. To account for the possibility that the coefficients may vary over

[14] We describe details of this procedure in Appendix A.2. Appendix Figure A.1 shows some examples of the urban units in large and small cities.

time and across cities, we estimate (7) separately for each prefecture city, and separately for two time periods: 2007-2010 and 2011-2019. Since specification (7) requires enough data to precisely estimate, we restrict our estimation to cities and periods in which we observe at least 80 (120) industrial land sales as well as 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 specification (7), we can then predict residential prices for industrial parcels by plugging characteristics of these parcels into Eq. (7):

$$\hat{p}^{res}_{i,t} = X_{i,t}\hat{\beta}^{res} + \hat{\gamma}^{res}_{u,t},\ \forall i \in \mathcal{I}_{ind}. \tag{8}$$

That is, $\hat{p}^{res}_{i,t}$ 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 (7):

$$p_{i,t} = X_{i,t}\beta^{ind} + \gamma^{ind}_{u,t} + \epsilon_{i,t},\ \forall i \in \mathcal{I}_{ind}. \tag{9}$$

We then predict the counter-factual industrial prices for residential parcels as:

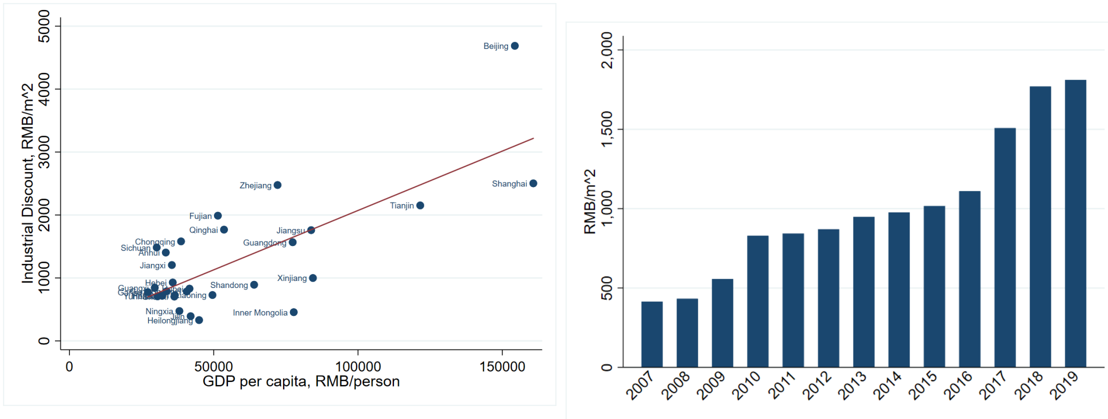
$$\hat{p}^{ind}_{i,t} = X_{i,t}\hat{\beta}^{ind} + \hat{\gamma}^{ind}_{u,t},\ \forall i \in \mathcal{I}_{res}. \tag{10}$$

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

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

In words, $\mathrm{IndDisc}_{it}$ is the actual (predicted) residential sale price minus the predicted (actual) industrial price for residential (industrial) parcels, where the residential prices are adjusted by $1 - \lambda = \frac{2}{3}$ (recall Section 3.1).

The estimation delivers $\mathrm{IndDisc}_{i,t}$ at the land parcel level. We then aggregate to form city-year level estimates, $\mathrm{IndDisc}_{c,t}$, by taking averages of $\mathrm{IndDisc}_{i,t}$



(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.

weighted by the size of each land parcel. Figure 2 Panel (a) shows the industrial discounts are higher 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 and increased to 750 RMB/m^2 around 2010. It remained stable during 2010-2015, but increased significantly during 2016-2019. In 2019, the average industrial discount reached about 1,800 RMB/m^2, four times the level in 2007. [15]

4.2 Industrial Tax Estimation

4.2.1 Estimation Methodology

In this section, we discuss how we estimate the effects of land purchases on firms' sales using a differences-in-differences approach. Suppose that in period τ_j, firm j purchases a land parcel of size Δ_j. Define $\Delta_{j,t} \equiv \Delta_j \cdot \mathbf{1}_{t \geqslant \tau_j}$; then firm j's sales in

[15] 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 residential land price increased by a factor of about 3.12 and the industrial land price barely changed during the same period.

period t take the following form:

$$S_{j,t} = \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \Delta_{j,t} + \varepsilon_{j,t}. \tag{11}$$

In words, Eq. (11) states that firms' sales are determined by time-varying factors η_t, time-invariant firm-specific factors α_j, and land purchases $\Delta_{j,t}$, whose effect depends on a parameter $\theta_{t-\tau_j+1}$. The time-varying factors η_t may represent, in reduced form, factors such as growth, demand, and input prices, while α_j represents persistent firm-specific productivity differences.

In this framework, treated firms are those that ever acquired some new industrial land during their presence in the sample either through auctions or agreements, i.e., firms with $\Delta_j > 0$ for some $2007 \leqslant \tau_j \leqslant 2013$. For cleaner identification, we focus on the sample of firms who have purchased land only in one year in our sample period.[16] 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.

A natural concern with estimating the parameters $\theta_{t-\tau_j+1}$ in Eq. (11) is that land purchase decisions may be endogenous with firm-time-specific shocks $\varepsilon_{j,t}$. To address this concern, we decompose these shocks as

$$\varepsilon_{j,t} = f(p(x_{j,t})) + e_{j,t}. \tag{12}$$

In this decomposition, f can be any function, and $p(x_{j,t})$ is a firm's probability of purchasing land given observables $x_{j,t}$. We make the identifying assumptions:

$$\mathbb{E}[e_{j,t}\Delta_{j,t} \mid \alpha_j, \eta_t, \tau_j \in \{\tau, \infty\}] = 0 \quad \text{and} \quad \mathbb{E}[e_{j,t}\mathbf{1}_{\Delta_j>0} \mid \alpha_j, \eta_t, \tau_j \in \{\tau, \infty\}] = 0, \; \forall \tau \tag{13}$$

In words, the two requirements for $e_{j,t}$ are that these shocks to firm sales be uncorrelated (i) with the amount of land purchased and (ii) with the decision of whether to buy 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 that these assumptions only need to hold after we control for firm and time fixed effects. Because $e_{j,t}$ is the component of firm-time-specific shocks that

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

are *unrelated* to the probability of land purchase predicted by $x_{j,t}$ (see Eq. (12)), we view this as a plausible identifying assumption, and moreover an assumption that we can partially test by examining pre-trends in sales among treatment and control firms.

Motivated by this framework, we match treated firms with control firms using propensity scores $\hat{p}(x_{j,t})$ for land purchase using firm characteristics in year $t = \tau_j - 1$. Recall that the control firms are those that did not acquire any new industrial land during their presence in the sample. After stratifying by event year, province, and two-digit National Industries Classification code, we estimate $\hat{p}(x_{j,t})$ based on the three following observables at the firm level:

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

Here, $S_{j,t}$ is firm j's sales in period t and $\mathtt{Profit}_{j,t}/S_{j,t}$ is firm j's profit margin in period t. In our data, we find these three variables are predictive of land purchase decisions; other observables do not provide additional explanatory power for whether the firm purchases land in $t = \tau_j$.

After matching, one test of our assumption on the residuals $e_{j,t}$ will be whether treated firms and control firms exhibit parallel trends in sales prior to τ_j. We conduct this test as part of our differences-in-differences strategy 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

$$\bar{\Delta}_\tau \equiv \mathbb{E}\left[\Delta_j \mid \Delta_j > 0,\ \tau_j = \tau\right], \tag{14}$$

which essentially estimates the average land size at a particular year τ by averaging over land transactions in that year. Using Eq. (11), firm sales can be equivalently written as

$$S_{j,t} = \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \mathbf{1}_{\Delta_j>0} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}, \tag{15}$$

where we define

$$\varepsilon'_{i,t} \equiv \begin{cases} \varepsilon_{j,t}, & \Delta_{j,t} = 0; \\ \varepsilon_{j,t} + \theta_{t-\tau_j+1} \cdot (\Delta_{j,t} - \bar{\Delta}_{\tau_j}), & \Delta_{j,t} > 0. \end{cases} \tag{16}$$

Note that,

$$\mathbb{E}[\varepsilon'_{j,t}\bar{\Delta}_{\tau_j} \mid \alpha_j, \eta_t] = 0, \tag{17}$$

where we use conditioning on α_j and η_t to reflect controlling for firm and time fixed effects. This follows from (13) thanks to the definition of $\bar{\Delta}_{\tau_j}$ in Eq. (14). In light of Eq. (17), we can consistently estimate $\theta_{t-\tau_i+1}$ with difference-in-differences estimation using regression specification (15).

4.2.2 The Effect of Land Purchase on Sales

Table 2 reports the estimates of specification (15). We take the year $t = \tau - 1$ to be the base year. In all regressions we also allow the time fixed effects η_t to vary at the province-year level, i.e., $\eta_{p,t}$, to absorb differences in time trends across provinces.

For each purchase year $\tau \in \{2007, 2008, 2009, 2010\}$, we use data from years $\tau - 4$ (there are very few firms with data before $\tau - 4$) through the year 2013. We start from 2007 which is the first year of the land sale data; we end in 2010 which is the last land purchase year for which we observe firm tax data after two years (i.e., 2013) to estimate the permanent impact of land purchase on taxes as in Table 3.

Table 2 reveals three important patterns. First, estimated treatment effects are positive and are both economically and statistically significant. Each square meter of land generates, for example, 428.2 RMB in additional 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 the event. Note, our matching procedure guarantees that the parallel trend holds between the treated and control firms from $t = \tau - 2$ to $t = \tau - 1$. The fact that the parallel trend 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

Table 2: Dynamic Treatment Effect of Land Purchase on Sales

Event Year τ	2007	2008	2009	2010
Dep Var: Sales	(1)	(2)	(3)	(4)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = -4)$	192.9	-77.30	-17.82	141.4
	(0.562)	(-0.110)	(-0.0717)	(0.444)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = -3)$	2.781	185.0	-105.7	339.4
	(0.0143)	(0.337)	(-0.534)	(1.568)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = -2)$	10.21	-107.3	69.11	191.5
	(0.0936)	(-0.363)	(0.554)	(1.558)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 0)$	428.2***	938.1**	287.3**	
	(2.869)	(2.257)	(2.133)	
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 1)$	783.3***	1,097**		772.3***
	(3.235)	(2.486)		(2.695)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 2)$	687.0**		655.6**	1,048***
	(2.207)		(2.129)	(2.985)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 3)$		1,691**	602.9*	1,497***
		(2.070)	(1.678)	(3.299)
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 4)$	814.2*	2,222*	965.8**	
	(1.847)	(1.725)	(2.333)	
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 5)$	1,293*	1,600		
	(1.757)	(1.059)		
$\bar{\Delta} \cdot \mathrm{Treat} \cdot (t - \tau = 6)$	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 (15) with the matched sample. We drop the 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 is 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

more concisely. In words, 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, which captures the more modest effects on sales that we observe as firms presumably are making other fixed investments (e.g., new plants) that complement the land purchase, and another treatment effect for the third and subsequent years after purchase, which captures the long-run effects of new land. Formally, we estimate

$$S_{j,t} = \alpha_j + \eta_{t,\tau_j} + \theta_{\text{short}} \cdot \mathbf{1}_{\Delta_j>0,t-\tau_j\in\{0,1,2\}} \cdot \bar{\Delta}_{\tau_j} + \theta_{\text{long}} \cdot \mathbf{1}_{\Delta_j>0,t-\tau_j>2} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}. \quad (18)$$

In the first column 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 next four columns we report the estimated effects year-by-year.

Overall, we observe that in the first three years after land purchase, land sales generate an additional 636.2 RMB/m^2 in sales on average per year; and in subsequent years after land purchase, land sales generate a long-run effect of 1199 RMB/m^2 in sales on average per year.[17]

Before leaving this section we discuss one econometric issue regarding panel imbalance. Firms enter and exit our panel due to data linkage issues. For example, we use firm names as firm identifiers, so name changes or inconsistencies in name reporting 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 Appendix C.2 we study the causes of panel imbalance and conclude the majority of imbalance is due to idiosyncratic data linkage issues. We also find evidence that a modest amount of imbalance is due to censoring, which we argue in Appendix C.2 makes our estimates of land-purchase treatment effects conservative.

4.2.3 Firm Tax Estimation

We now calculate the marginal tax revenues generated by firms' land purchases. Although in Section 4.2.2 we only estimate the increase of sales of the land-

[17] As the data for 2010 is missing, we lack one year of observations for either the first three years or the later years, depending on the land purchase year τ.

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)
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau \in \{0, 1, 2\})$	636.2***	561.7**	1,003**	393.6**	751.3**
	(4.367)	(2.562)	(2.205)	(2.327)	(2.352)
$\bar{\Delta} \cdot \mathtt{Treat} \cdot (t - \tau > 2)$	1,199***	1,283**	1,836*	736.3**	1,342***
	(4.453)	(2.050)	(1.745)	(2.073)	(2.887)
Firm FE	Yes	Yes	Yes	Yes	Yes
Province-Year FE		Yes	Yes	Yes	Yes
EventYear-Province-Year FE	Yes				
Observations	43,671	9,425	4,196	13,171	16,879
R^2	0.505	0.439	0.548	0.561	0.488

Note: This table reports estimation results of Model (18) 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 is 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

purchasing firms, the tax estimation goes beyond the land-purchasing firm and incorporates general equilibrium effect.

The most important taxes paid by industrial firms are value-added taxes and corporate income taxes, with both being approximately linear functions of the firm's value added.[18] If we assume homogeneous relationship between taxes and value added across firms, then the total increase of taxes due to a single firm's land purchase equals the total increase of value added times the effective tax rate.

In this paper we approximate the total increase of value added to the economy due to the purchase of an industrial land parcel by the total increase of sales of that land-purchasing firm. By definition, the sales of the land-purchasing firm equal the sum of value added of 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 the downstream firms and competing firms. To sign the externality, Appendix C.3 presents a simple model with perfect competition, which builds on Hulten (1978) and Baqaee and Farhi (2019). Our analysis shows that the increase in land

[18] For a detailed description of the system of firm taxation in China, see Appendix C.4.

buyers' output will over-estimate changes in total output, if land purchases lead land-buying firms to increase their input purchases. Essentially, this is because land buyers cannibalize input purchases, and hence decrease output of other firms.

Therefore, under the framework of Hulten (1978) and Baqaee and Farhi (2019) with perfect competition, our treatment tends to over-estimate the total effect on value added to the economy. However, in practice, the product markets in China could be far from competitive. To our best knowledge, there is no standard solution in the literature to address the bias, and we will leave this to future studies.

So what remains is the estimation of the effective tax rates. We estimate the industrial firm tax rates in China in Appendix C.4. As shown in Figure A.3, the average value-added tax rate, which is approximately 12.10%, is relatively stable for firms of different sizes. We also estimate that income taxes and other administrative fees amount to approximately 5.77% of firms' value added. Combining these estimates, firms face an average tax rate of approximately 17.87%.

Now we obtain the marginal effects of land purchase on tax revenues, by multiplying the tax rate with the estimated effect, 17.87%, on sales from column (1) of Table 3. Recall we have assumed that incremental tax cash flows start one year after the sale of industrial land (which occurs at the beginning of that year). Therefore, for industrial land sale in year $t-1$ (i.e., at the beginning of year t), the industrial tax cash flows in year s is:

$$\mathrm{Tax}^{ind}_{t-1,s} = 636.2 \times 17.87\% = 113.6 \text{ RMB}, \text{ for } s-t \in \{0,1,2\} \tag{19}$$

$$\mathrm{Tax}^{ind}_{t-1,s} = 1199 \times 17.87\% = 214.2 \text{ RMB}, \text{ for } s-t > 2 \tag{20}$$

4.2.4 Complementary Evidence

Our estimates of marginal tax income of industrial land sales square nicely 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 tax receipts to the average VAT per square meter of land. For each province during our sample period, we calculate the average VAT per square meter of land as total VAT revenue from China Tax

Yearbook,[19] divided by total industrial land size (from China City Construction Yearbook). Appendix Figure A.4a shows the average VAT income per square meter of land for each province in 2011, a year that is right after the sample period of 2007-2010 that we use to estimate the marginal taxes on 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 revenues per square meter of land, 214.2 RMB/m^2 in Eq. (20).

Official guidance on minimum required tax on industrial land. As the second source of evidence 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 initiated the Guidelines on Land Supply to Industrial Projects, which required the local land bureaus to impose restrictions on the industrial land supply along certain dimensions (for example, a green land ratio).[20] Some provincial land bureaus modified the guidelines by adding additional requirements on the tax payment by firms, with Jiangsu province being the first to explicitly impose an industry-specific minimum requirement on tax payments by firms on industrial land in 2018. Some provinces, such as Hunan, followed and imposed the same minimum requirement in 2020.

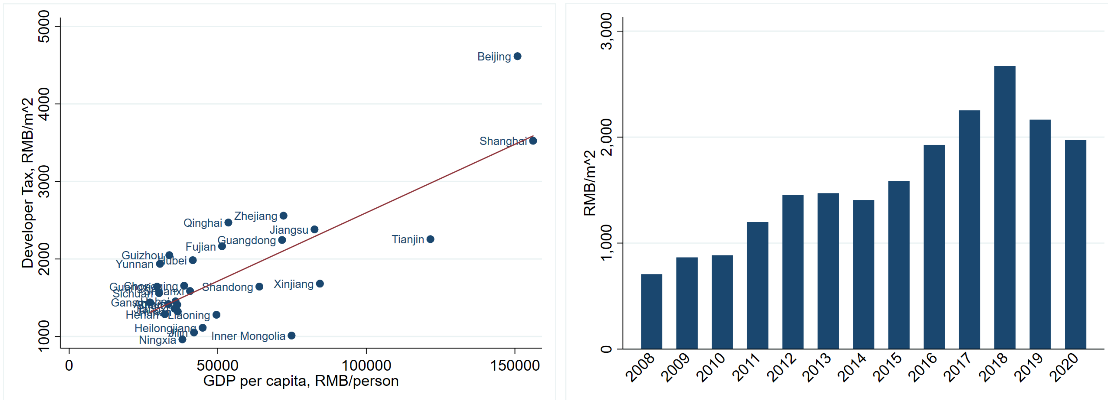
Appendix Figure A.4b plots the industry-specific minimum requirement on annual tax payments set by Jiangsu and Hunan province for all manufacturing industries. The minimum tax requirement for most industries is around 100 RMB/m^2, and if we average across industries using the industrial composition of land sales in our data during 2007-2010, we find an average minimum tax requirement of 113.6 RMB/m^2. We thus conclude our estimate of the marginal tax revenues of 214.2 RMB/m^2 accords with these minimum requirements.

4.3 Developer Tax Estimation

Finally, we estimate the increase in taxes paid by residential developers induced by residential land sales. Since there are no residential property taxes in China, these one-time incremental taxes paid by developers are the only channel through

[19] 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.

[20] 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.



(a) Prov. Developer Tax vs GDP Per Capita

(b) Developer Tax over Time

Figure 3: Developer Tax Estimates Summary.

Note: Panel (a) plots the province-level average home developer 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 developer tax estimates across cities for each year from 2008 to 2020.

which residential land sales increase tax revenues. The tax revenue collected per square meter of residential land in city c and year t can be expressed as:

$$\mathsf{DevTax}_{t,c} = P^{h}_{t,c} \times \mathsf{FloorRatio}_c \times \mathsf{DevTaxRate}_t, \tag{21}$$

where $P^{h}_{t,c}$ is the average house price per square meter of livable space; $\mathsf{FloorRatio}_c$ is the average amount of livable space that is built per square meter of residential land; and $\mathsf{DevTaxRate}_t$ is the expected amount of taxes developers pay, for each RMB increase in their total sales in year t.

We calculate $P^{h}_{t,c}$ using total house sale revenues divided by the total construction area of houses sold in city c and year t. 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. To get $\mathsf{DevTaxRate}_t$, we use data of listed developers in year t and regress the firms' total annual taxes on annual sales.[21] Appendix Figure A.5 shows the relationship between the listed developers' annual taxes against their sales. The relationship is

[21]Since May 1, 2016, home developers start to pay value-added taxes, which is not reported in their income statements. We estimate the value-added taxes using (Sales-COGS)$\times$ VAT tax rate and then add it to the reported taxes.

close to linear year by year, suggesting that $\mathrm{DevTaxRate}_t$ is roughly independent of developer size.

Figure 3 Panel (a) shows that in provinces with higher GDP per capita, home developers pay more taxes per square meter of land. Panel (b) shows that the average taxes paid by developers, per square meter of land, is increasing over time.

4.4 IRR^{ind} Estimates

In this section, we use the framework of Section 3 to translate our empirical estimates into an IRR estimate on industrial land sales. 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 the IRR 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 $\mathrm{IndDisc}_{c,t}$ during 2007-2010 and $\mathrm{DevTax}_{t,c}$ during 2008-2011, weighted by the area of land purchased by the 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 developer taxes during 2008-2011 is 1453.03 RMB/m^2. Combining this with the estimates of industrial tax revenues, which are 113.6 RMB/m^2 in the first two years given by Eq. (19) and 214.2 RMB/m^2 thereafter given by Eq. (20), we calculate the government IRR in Eq. (3) to be $\mathrm{IRR}^{ind} = 7.70\%$. We emphasize that all inputs in this calculation are based on their respective sample periods and hence do not suffer the usual "look-ahead" bias.

One of the main takeaways from our paper is that our estimate of IRR^{ind} is not smaller than most estimates of government discount rates in the literature, which we will 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

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

	IndDisc	Tax^{ind}		Tax^{res}	IRR^{ind}
Baseline	1012.83	113.67	214.23	1453.03	7.70%
Exclude Five-Yr-Plan-Targeted industries	991.55	98.89	171.77	1380.74	6.57%
Full Tax Deduction	1012.83	85.25	214.23	1453.03	7.33%
Two-year gap of $DevTax$	1012.83	113.67	214.23	1765.69	6.93%
Combination of three adjustments	991.55	74.17	171.77	1713.68	5.60%

Note: This table shows the industrial land discount estimates during 2007-2010, the tax benefits, and the corresponding IRR^{ind}, calculated with Eq. (3). We aggregate the city-year level industrial discount estimates and developer taxes to the national level, all using the weight proportional to the area of land purchased by the treated firms in that city-year when we estimate Column (1) in 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 non-targeted industries to match the industrial tax estimation.

the provincial and the city level.[22] Since the "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 selling land directly (Bai et al., 2016; Chen et al., 2020), and their market-determined yields reflect the city governments' fiscal conditions.[23]

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%. This finding suggests that city governments' sharing of tax revenues with higher-level governments plays an important role in the equilibrium land allocation decisions. To see this, if the city government received the entirety of industrial tax revenues, then the discussion

[22] 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).

[23] We do not use the yields of municipal bonds for two reasons. First, the 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.

of governments' market power over residential and industrial land in Section 3 (see Eq. (5)) indicates that $\mathrm{IRR}^{\mathrm{ind}}$ should be smaller than city governments' cost of capital. In contrast, the fact that city governments only retain a fraction of tax revenues can explain why $\mathrm{IRR}^{\mathrm{ind}}$ is comparable to r^{gov}.[24]

In sum, guided by the simple economic framework developed in Section 3.2, our estimated $\mathrm{IRR}^{\mathrm{ind}}$ leads us to highlight the intersection of three forces that drive the IRR on industrial land sales in China: the "land finance" system, in which the revenues from land sales accrue entirely to city governments and are an important source of governments' operational funds; the distinct time profiles of revenues from industrial and residential land sales along with the governments' discount rates; and the asymmetric treatment of industrial tax revenues, which are shared between city governments and upper-level governments. The last two points are new to the literature on the price discounts on industrial (versus residential) land, and Section 5 conducts cross-sectional analysis to provide further evidence that industrial discounts are associated with cities' discount rates as well as their shares of industrial tax revenues.

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 Eleventh or Twelfth Five-year Plans, which highlights the key sectors the government plans to support during the period 2006-2015 (Cen et al. (2021)).[25] 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 the cost of these policies. In our sample, among all the treated firms, 57.0% (43.0%) are from targeted (non-targeted) industries and they account for 62.7% (37.3%) of the size of the matched industrial lands.

We estimate $\mathrm{IRR}^{\mathrm{ind}}$ for targeted industries to be 8.05% (unreported), which is

[24] In Appendix B, we consider an alternative assumption that the cash flow is not constant perpetuity but grows at a constant rate g. In this case, the measured IRR is the same as Eq. (5) except r^{gov} is replaced by $r^{gov} - g$. This implies that the growth of industrial taxes g, which tends to make implied $\mathrm{IRR}^{\mathrm{ind}}$ lower, plays the opposite role of the city tax sharing k.

[25] Table C.7 in the appendix shows the list of targeted industries.

indeed modestly higher than the IRR of 6.57% for non-targeted industries. Thus, accounting for industrial policy-targeted industries does not substantially affect our IRR estimates.

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 7.70% to 7.33%.

Third, we consider an alternative assumption on the timing of the developer tax cash flows, i.e., the developer taxes all occur two years following the land acquisition. The estimated average developer taxes increase to 1765.69 RMB/m^2, and the IRR reduces modestly to 6.93% as shown in the fourth row.

In the last row, we consider the two subsidy policies together and the alternative timing of developer tax cash flows and further estimate IRR for non-target industries to be 5.60%, 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. We cannot directly estimate industrial taxes for industrial land sold after 2010, since we do not have a long enough panel to estimate our differences-in-differences specification. However, under the assumption that industrial taxes per square meter of industrial land stay the same before and after 2010, we can use our yearly estimates of industrial land discounts and the developer 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_t^{ind} along with the city government's discount rates proxied by the average MCB yields. The IRR^{ind} was stable during 2010 and 2015 and varied between 5.0% and 6.5%, which is still comparable to the MCB yields. The IRR^{ind} decreased substantially since 2016 and was about 3.80% in 2019, which dips below the government discount rates.

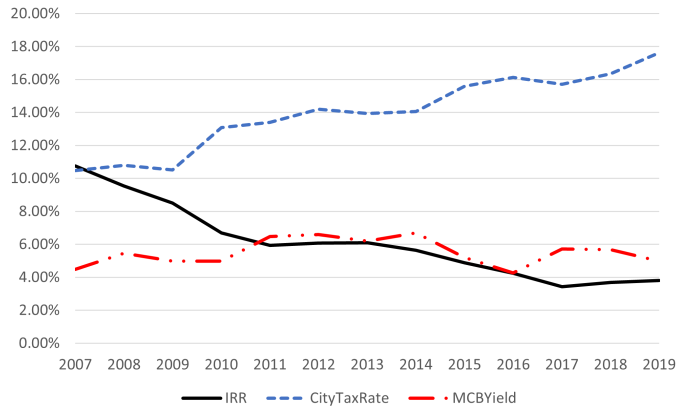


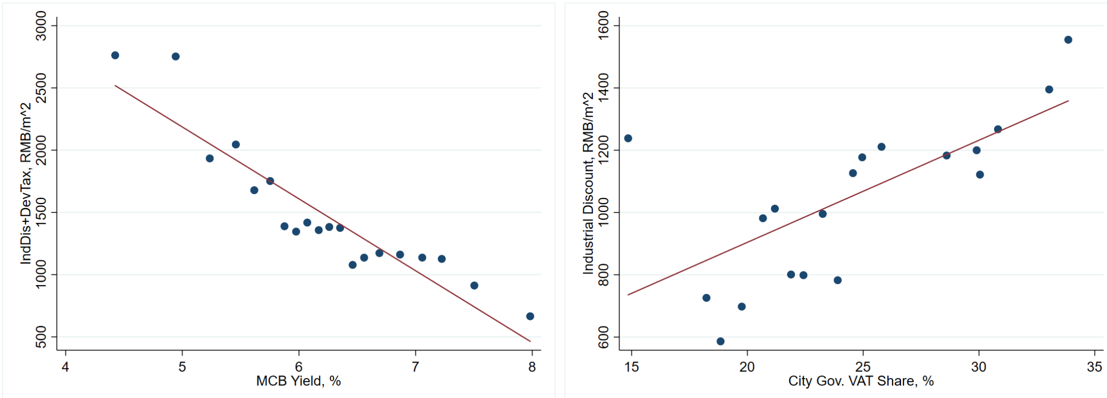
Figure 4: Industrial Discount and IRR

Note: This figure plots: (1) the time series of IRR^{ind} (in black solid line), calculated by holding the tax benefits constant as in Eq. (19) and (20) and using the yearly estimates of industrial discounts and developer taxes; (2) the effective tax rates that accrue to the city governments (in blue dotted line); and (3) the average MCB yield (in red dash-dotted line), calculated as MCB issuance yield weighted by issuing amount for each year.

As implied by Eq. (4) in Section 3.2, the decreasing trend of IRR^{ind} is most likely explained by the increasing trend of city governments' tax share. Indeed, Figure 4 shows the increasing trend of the effective tax rates that accrue to the city governments, estimated by regressing the annual change of the city government fiscal revenues plus central transfers on the annual change of the city GDP. We will show shortly in Section 5.2 that this pattern also holds in cross section.

5 City Discount Rates and Tax Sharing

So far, we have shown the quantitative importance of industrial taxes in local governments' land allocation decisions. In this section, we provide causal evidence that industrial taxes do affect the land allocation decisions, by exploiting cross-city heterogeneity. Recall the theoretical framework in Section 3.2, where we derive $\text{IRR}^{ind} = r^{gov}/k$ in Eq. (4) without considering demand elasticities. Since IRR^{ind} inversely relates to industrial discount, the framework predicts that industrial discounts should be negatively (positively) correlated with city government MCB yields r^{gov} (the city share of industrial tax revenues k). Figure 5 plots simple binscatters of MCB yields and VAT shares across city-years against



(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 $\texttt{IndDisc}_{ct}$ 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 $\texttt{IndDisc}_{c,t}$ against the city government's VAT share in year t for the sample period 2007-2019.

industrial discounts; both predictions hold empirically. We proceed to analyze these relationships in detail.

5.1 Government Discount Rates

A concern for interpreting Figure 5 Panel (a) is that MCB yields may be endogeneous: certain forces may affect both MCB yields and industrial discounts, so the cross-sectional correlation between MCB yields and industrial discounts may not reflect the causal effect of government discount rates on industrial discounts. To address this concern, we build on Chen et al. (2020) and use an instrumental variable for MCB yields related to China's four-trillion stimulus plan in 2009. The instrument uses local political officials' job tenure at the launch of the stimulus; Chen et al. (2020) show that cities in provinces with governors who were late in their term engage in more local infrastructure investment in 2009, which has long-lasting effects on the local government's fiscal position in the future and hence on future bond yields. 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.[26]

Following Chen et al. (2020), we construct an instrument, $\mathsf{LateTerm}_c$, which equals one if the city c's provincial governor had been in office for at least three years in the beginning of 2009, and zero otherwise. The first stage is strong and statistically significant: $\mathsf{LateTerm}_c$ is negatively correlated with the MCB yield in subsequent years, and in particular during the period 2012-2019; the first-stage F-statistic for this time period is 28.1. This negative sign is consistent with greater infrastructure investment in 2009 leading to a stronger future fiscal position, for example in the form of greater land reserve values (both for sale, and for the government to use as collateral). The exclusion restriction for the instrument is that these fiscal changes are only correlated with the future industrial discounts through changes in MCB bond yields. In particular, the exclusion restriction requires that the size of a city's land reserve, which can be developed for both industrial and residential purposes, does not directly affect the choice of what mix of residential or industrial land to sell.[27]

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:

$$\mathsf{IndDisc}_{c,t} = \beta \times \mathsf{MCBYield}_{c,t} + \sum_{\tau} \gamma'_{\tau} \cdot \mathbf{1}_{t=\tau} \cdot X_{c,2008} + \epsilon_{c,t}, \qquad (22)$$

where $\mathsf{MCBYield}_{c,t}$ is the average yield of MCB bonds issued by city c year t and weighted by issuance amounts.[28] To separate our estimation sample from the potential direct effect of the governor's term in 2009, we estimate Eq. (22) based

[26]More broadly, this instrumental variable is motivated by 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 his or her provincial governor's political agenda, because of China's "one-level-up" policy: the promotion of the local officials is largely determined by their immediate superior officials (Chen and Kung, 2019).

[27]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 reserves mentioned here.

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

Table 5: Industrial Discount and Municipal Corporate Bond Yield

Specification	OLS	OLS	IV	IV
Dep Var: IndDisc	(1)	(2)	(3)	(4)
MCBYield, %	-577.5***	-416.7***	-1,823***	-2,371***
	(-9.105)	(-6.908)	(-7.472)	(-4.085)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,547	1,545	1,547	1,545
R-squared	0.326	0.401	-0.783	-1.652
#City	277	276	277	276
F statistic			32.68	12.67

Note: This table shows the regression of industrial land discounts 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 $\mathtt{LateTerm}_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

on the sample period 2012-2019.[29] We control for time-varying effects of initial city-level economic conditions using $X_{c,2008}$, which includes the 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 results are shown in Table 5. The first two columns report OLS estimation results, confirming the negative correlation in Figure 5. In Column (3) and (4), we instrument $\mathtt{MCBYield}_{c,t}$ with $\mathtt{Lateterm}_c$ and find a significantly negative causal effect of bond yield on the industrial discounts.[30]

The association between bond yields and the upfront industrial discounts highlights how city governments' land allocation decisions can be entangled with their liquidity management. City governments with more liquidity shortfall or greater financial constraints may reallocate land sales from industrial to residential

[29] One concern regarding the exclusion restriction is that the governor term in 2009 would predict the terms of future provincial governors, which could have a direct effect on the land supply. Chen et al. (2020) show that thanks to the anti-corruption campaign launched in 2012 by Xi Jinping, there is negligible correlation between governor term in 2009 and in future years after 2012.

[30] In appendix D.2.2, with the same specification as Eq. (22), we also find a significant and negative causal effect of the MCB yields on the city's upfront developer taxes.

uses, trading future cash flows from industrial taxes to more immediate cash flows from residential sales—as well as the developer taxes—under the "land finance" system. While these patterns are evident across geography, they also may matter over time, suggesting if distress were to emerge in the Chinese municipal bond market, reductions in industrial land supply (absent any tax reform to correct for this) may be an important knock-on effect.

5.2 City Tax Shares

As we discussed in the previous section, the fact that IRR^{ind} is at the high end of the city government discount rate during 2007-2010 suggests that city governments do not fully internalize the tax revenues generated from industrial land. In this subsection, we investigate the relationship between industrial discounts and the share of value-added taxes that accrue to city governments.

The central government gets a uniform share of value-added taxes across provinces, and 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 accruing to the city governments in different provinces.[31] 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, we assume 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 takes 75% of the value-added taxes and the remaining 25% goes to the provincial and city governments. On May 1, 2016, the central government launched a major tax code change–the so-called "Business to Value-added" program—which enlarged the coverage of value-added taxes. More importantly, this reform modified the tax-sharing scheme, such that the share of

[31] 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 less state-owned firms controlled by the province governments.

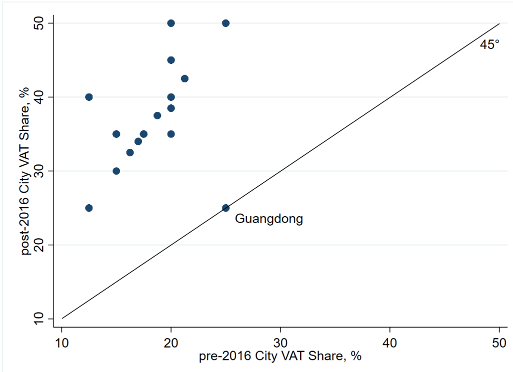
value-add taxes retained by the local governments increased from 25% to 50%.[32] The province-level government would then decide how to split the incremental 25% of the value-added taxes between itself and the city governments. The differential increase of the city's VAT share in 2016 provides an opportunity 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 a rise 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).

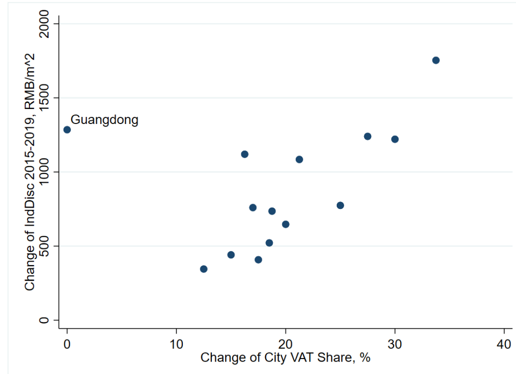
In both panels of Figure 6 we observe that the cities in Guangdong province appear to be outliers. Although they experienced zero increase in their share of VAT, the industrial land discount increased substantially from 2015 to 2018 in these cities. One possible explanation is confounding policies that also encouraged industrial land supply in Guangdong. On August 20, 2017, the provincial government of Guangdong initiated a list of actions to secure the industrial land supply by the city government. All these actions are taken by Guangdong only, and are not in place before 2017. Appendix D.1 provides more details on the land-related policies for Guangdong province. Due to these factors, we remove Guangdong from our analysis in the rest of this section.

Dynamic Treatment Effect on Industrial Discounts. We apply a straightforward difference-in-differences estimation strategy to study how local governments' land

[32] Local governments previously received the entirety of business taxes. After the launch of this program in May 2016, the business taxes were replaced with value-added taxes and shared by the central government, and the central government 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.

allocation decisions respond to these changes in city VAT shares:

$$y_{c,t} = \alpha_c + \gamma_t + \sum_{\tau \neq 2015} \beta_\tau \times \mathbf{1}_{t=\tau} \times \Delta VATShare_c + \varepsilon_{c,t}, \tag{23}$$

for city c in year t, with city and year fixed effects. In Eq. (23), 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 (k) increases, they should be willing to offer a higher industrial land discount (a lower IRR^{ind}).[33] The estimation results reported in Table 6 support this hypothesis. We observe a significant and positive treatment effect on the industrial land discount

[33]There are two possible mechanisms through which the industrial discount adjusts. First, the city government may allocate more industrial land relative to residential land in the future, with an immediate adjustment in prices (and hence industrial discounts). The quantity adjustment may not occur in the short run given the planning constraint; see Section 2. Second, if the government and the potential buyers can negotiate on the land transaction, the buyer who knows that more future taxes go to the local government may ask for a greater industrial discount.

in all the 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.

Table 6: City VAT Share and Industrial Land Discount

Dep Var:		IndDisc	$(1-\lambda)p^{res}$	p^{ind}
		(1)	(2)	(3)
$\Delta VATShare\times$				
Year=	2011	-8.757	-12.63*	-3.875
		(-1.191)	(-1.748)	(-1.430)
	2012	-0.156	-1.965	-1.810
		(-0.0136)	(-0.188)	(-1.032)
	2013	-7.850	-8.592	-0.742
		(-0.990)	(-1.108)	(-0.701)
	2014	-1.192	-0.603	0.589
		(-0.0790)	(-0.0390)	(0.605)
	2016	21.80***	20.53***	-1.273**
		(3.163)	(2.976)	(-2.055)
	2017	43.42***	41.42***	-2.001***
		(3.941)	(3.705)	(-2.605)
	2018	26.25**	25.10**	-1.148
		(2.276)	(2.156)	(-0.855)
	2019	34.17***	33.84***	-0.325
		(3.133)	(3.059)	(-0.266)
Observations		2,320	2,320	2,320
R-squared		0.821	0.836	0.805
Year FE		Yes	Yes	Yes
City FE		Yes	Yes	Yes
#City		258	258	258

Note: This table shows how the change in city VAT share affects industrial land discounts. The sample includes all the municipal cities for which we have the industrial discount estimates from 2011-2019, and the year 2015 is used as the baseline. The treatment variable, $\Delta VATShare$, is in percentage. Standard errors are clustered by cities. Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Columns (2) and (3), we investigate the industrial and residential land price separately. Consistent with our framework, the increase of industrial tax share increases the residential and reduces the industrial land price. In terms of magnitude, the effect is mostly driven by the increase of the residential land price.

This could be because the demand elasticity for industrial land is higher than that for residential land. Industrial firms typically shop around different cities for the most favorable land price, but most households do not move across cities and demand for residential land is more fixed; therefore, residential land prices shall adjust in a significant way when the supply changes.

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 the city governments. We confirm this prediction in Appendix D.2.3.

Discussion on Economic Magnitudes Table 6 allows us to gauge the importance of city VAT share in explaining the observed industrial land discounts. From 2015 to 2019, the city's share of VAT increases by about 21.2%; combining this value with the treatment effect in 2019, 34.17, this VAT share change would predict an increase of industrial discounts by 724.4 RMB/m^2. For comparison, the realized increase of industrial discounts from 2015 to 2019 was about 762.5 RMB/m^2.

We can also link the magnitude of the estimated effect in regression model (23) to the marginal value-added tax revenue of industrial land estimated in Section 4.2.3, which is 77 ($= 636.2 \times 12.10\%$) RMB/m^2 in the first three years and 145 ($= 1199 \times 12.10\%$) RMB/m^2 permanently afterwards. If we take the average government borrowing rate of 5.25% (i.e., average yield of MCBs issued by 2019) as a proxy for the government discount rate, then the present value of total value-added tax revenue is 3824 RMB/m^2 and an increase of 1% in city VAT share allows the city government to get 38.24 RMB/m^2 more in taxes from industrial land. This is smaller than but comparable to our estimate in Table A.7 in the appendix, where we find a 1% increase in city VAT share is associated with an increase of 50.18 RMB/m^2 (if we combine the three post-treatment years 2017-2019) in industrial land discount plus the city's developer taxes.

Together, the results suggest that the city governments' share of tax revenues does affect the land allocation decisions: increasing the share of value-added tax revenues accruing to local governments increases the industrial land discount.

6 Conclusion

In this paper, we analyze the industrial land discount in the Chinese land market. Counter to conventional wisdom, the return of supplying industrial instead of residential land, accounting for all the future tax revenues, is at the high end of the usual range of government discount rates proxied by the MCB yields during 2007-2010. The return diminishes over time with the sharpest decline in 2016, which is most likely explained by the city governments' increasing share of local tax revenues, especially the 2016 tax reform that increased the city government share of value-added taxes. Cities with higher borrowing costs, which discount future cash flows by more, also exhibit a lower industrial land discount. Our results have implications for understanding the drivers of land prices in China, and how they are linked to the tax sharing scheme with the central government, as well as local governments' intertemporal revenue tradeoffs. From the central government's perspective, the tax sharing scheme between the central and local governments can be carefully designed to counteract the effect of the local governments' differential market powers in the local land market to achieve desired land allocation outcomes.

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Online Appendix

A Supplementary material for Section 2

A.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 NSIF database, collected by the Chinese National Bureau of Statistics. There is no consistent firm identifier in the NSIF 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 NSIF 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 C.2.

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 NSIF firms. In total, there are 19,602 unique merged firms that purchased land during 2007-2010 and 711,023 unique NSIF firms between 2003-2013. All variables except the last one in Panel 2 are measured in one million yuan.

A.2 Constructing Urban Units

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

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

There are 21,048 different urban units across the country. The median and mean of the total number of urban units in each prefecture city is 44 and 57, respectively. This large number is because, as Figure A.1 shows, there are many very small urban units. 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 Supplementary Material for Section 3

In this model, we decompose the IRR into government discount rate and the differential market power of the government between the residential and industrial land market. We will also show how the equilibrium industrial discount responds to the government discount rate and the share of industrial tax revenues accruing to the city government.

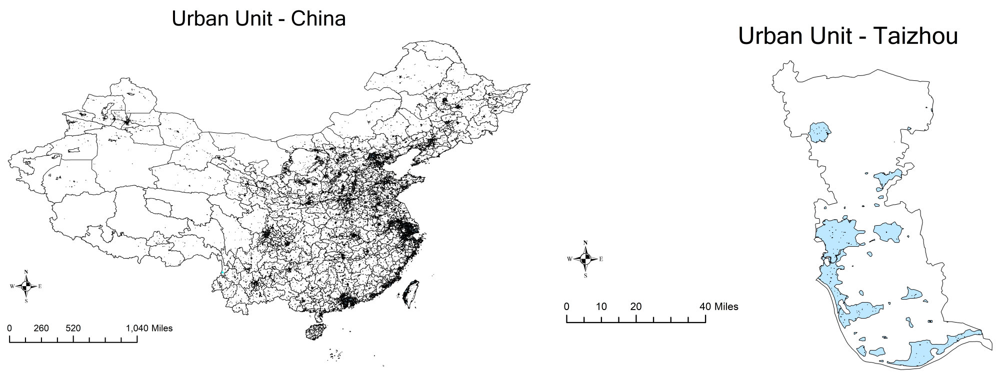


Figure A.1: Examples of Urban Units.

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.

The government allocates a fixed amount of land inventory $\bar{L}$ between residential use L_R and industrial use L_I. Denote the industrial tax rate as τ and the city's share of the industrial tax revenues as k. Assume the production function is $Y = f(L_I)$; the city's industrial tax revenue as a function of L_I is $k\tau f(L_I)$. Home developers also pay taxes due to home developing activities, and due to the strong correlation between residential land price and house price, we assume that the developer tax is $\tau^R \times P_R L_R$, and that all developer taxes go to the city governments. Denote the semi-elasticity of demand for residential (industrial) land as $-\sigma_R$ ($-\sigma_I$) and the government discount rate as r^{gov}. The city government's objective is to maximize the land sale revenues plus the present value of its own tax revenues:

$$\max_{L_I, L_R} \frac{1}{r^{gov}} k\tau \cdot f(L_I) + L_I P_I + (1+\tau^R) L_R P_R \text{ , s.t. } L_I + L_R = \bar{L}$$

Replace $L_R = \bar{L} - L_I$, and then the FOC with respect to L_I is:

$$0 = \frac{1}{r^{gov}} k\tau f'(L_I) + P_I - \sigma_I^{-1} - (1+\tau^R) P_R + \sigma_R^{-1} \tag{24}$$

Note that the residential land price facing buyers is $(1+\tau^R)P_R$ and hence $L_R \cdot \frac{d\ (1+\tau^R)P_R}{dL_R} = -\sigma_R^{-1}$.

Decomposition of IRR^{ind}**.** Equation (24) implies that in equilibrium, the marginal effect of land on tax revenues is:

$$\frac{k}{r^{gov}}\tau f'(L_I) = (1+\tau^R)P_R - P_I - (\sigma_R^{-1} - \sigma_I^{-1}) \tag{25}$$

The IRR can then be written as

$$IRR^{ind} \equiv \frac{\tau f'(L_I)}{(1+\tau^R)P_R - P_I} = \frac{r^{gov}}{k}(1 - \frac{\sigma_R^{-1} - \sigma_I^{-1}}{(1+\tau^R)P_R - P_I}) \tag{26}$$

Equation (26) decomposes the IRR^{ind} into three components. The first is the government discount rate r^{gov}. The second is the government differential market power in the residential and industrial market, which is captured by the difference of the inverse semi-elasticity scaled by the industrial discount plus developer taxes. The last term is k, i.e., the city government share of taxes.

If the government has no monopoly power in either land market, i.e., $\sigma_R = \sigma_I = \infty$, then

$$IRR^{ind} = \frac{r^{gov}}{k}.$$

Effect of Tax share k. Consider how the industrial discount changes when the government share of taxes, k, increases. Denote the price elasticity of demand for residential (industrial) land as $-\epsilon_R$ ($-\epsilon_I$) and assume they are constant. Then we can rewrite Equation (25) as:

$$\frac{k}{r^{gov}}\tau f'(L_I) = (1+\tau^R)P_R - P_I - (\frac{(1+\tau^R)P_R}{\epsilon_R} - \frac{P_I}{\epsilon_I}) \tag{27}$$

Taking derivatives with respect to k on both sides of Equation (27), we get:

$$\frac{d((1+\tau^R)P_R - P_I)}{dk} = \frac{\tau f'(L_I)}{r^{gov}} + \frac{k}{r^{gov}}\tau f''(L_I)\frac{dL_I}{dk} + \frac{d(1+\tau^R)P_R}{dk}\frac{1}{\epsilon_R} - \frac{dP_I}{dk}\frac{1}{\epsilon_I} \tag{28}$$

Equation (28) states that the effect of tax share on the industrial discount plus developer tax revenues equals the marginal tax revenues of the industrial land, plus the adjustment of the land allocation and the price impact on both the residential and industrial land market.

Consider an example where $f(L_I) = A \times L_I$. Assume the market for industrial land is competitive. The industrial land price would be $P_I = (1-\tau)A$. Equation

(28) simplifies to

$$\frac{d((1+\tau^R)P_R - P_I)}{dk} = \frac{1}{r^{gov}}\tau f'(L_I) + \frac{d(1+\tau^R)P_R}{dk}\frac{1}{\epsilon_R} \tag{29}$$

The increase of k will shift land allocation towards more industrial uses and less residential land uses, pushing up P_R. Therefore, both two items on the RHS of Equation (29) are positive. The increase of k will increase the upfront industrial discount plus the developer tax revenues.

Growth of Productivity. We have assumed no productivity growth and the industrial output to be at $f(L_I)$ forever. If the true model is that $f(L_I)$ grows at the rate of g, then in the equilibrium, the true IRR on industrial land sales would be

$$\tilde{IRR}^{ind} \equiv g + \frac{r^{gov} - g}{k}(1 - \frac{\sigma_R^{-1} - \sigma_I^{-1}}{(1+\tau^R)P_R - P_I}) \tag{30}$$

Our measurement of IRR assumes no growth, which turns out to be

$$IRR^{ind} \equiv \frac{r^{gov} - g}{k}(1 - \frac{\sigma_R^{-1} - \sigma_I^{-1}}{(1+\tau^R)P_R - P_I}) \tag{31}$$

C Supplementary material for Section 4

C.1 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".[34] Since we only have data on those numbers between 2010–2014 and we need to use

[34] 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.

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 the averages between years 2010–2012, which is in the middle of our data sample.[35]

For the auxiliary cost associated with providing public services to new residences, 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 $\lambda = 1 - \frac{1-\lambda_1}{1+\lambda_2} = 1/3$.

C.2 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

[35] 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.

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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.2 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.3 shows the survival rates of the treated and matched control firms for each event year, i.e., the percentage of firms remaining in the sample. By construction, all the firms are observed in the two years before treatment. There is not much difference between the treated and control firms in $t = \tau - 3$ and $t = \tau - 4$ in terms of the survival rates, confirming that the matching generates a comparable control group for the treatment group. However, after the treatment year, the survival rate of the treatment group is higher than that of the control group. This is consistent with the firm's expansion on the newly acquired land increasing sales and making the firm more likely to stay above the censoring threshold. While

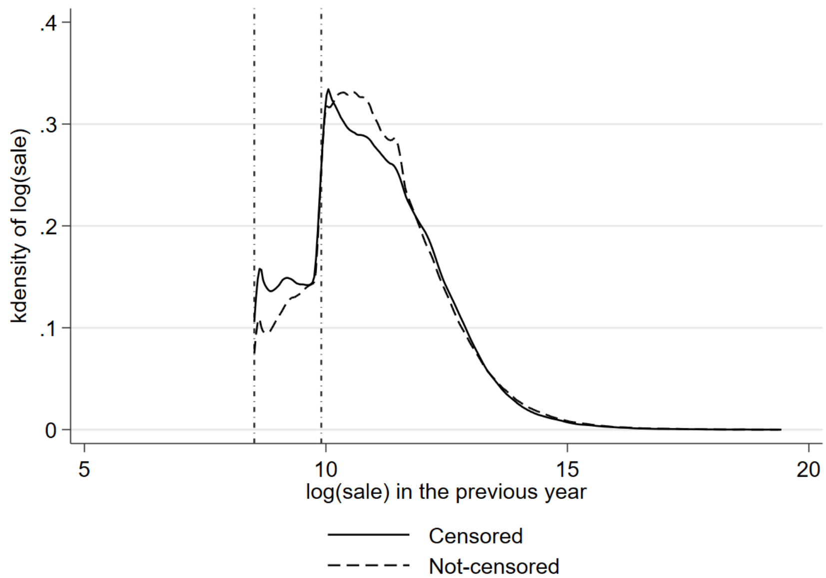


Figure A.2: Distribution of Log(Sale) in the Previous Year

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.

our evidence in Figure A.2 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.

C.3 The Impact of Land Purchases on Total Output 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

Table A.3: Survival Rates of the Matched Sample

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

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

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 inputs of good j used in the production of good 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

$$p_i \frac{dy_i}{dA_i} = p_i F_i + (\sum_f w_f \frac{\partial \ell_{i,f}}{\partial A_i} + \sum_j p_j \frac{\partial x_{i,j}}{\partial A_i}) \tag{32}$$

Thus, the increase in firms' sales, (32), will exceed the increase in total output, $p_i F_i$, as long as the difference term is positive:

$$(\sum_f w_f \frac{\partial \ell_{i,f}}{\partial A_i} + \sum_j p_j \frac{\partial x_{i,j}}{\partial A_i}) > 0 \tag{33}$$

The LHS of expression (33) 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.[36]

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, in response to increased productivity. When the first welfare theorem holds, the reallocation effects do not have a first-order effect on total output, since inputs are equally productive in all industries on the margin. Hence, the sales increase of the affected firm

[36]Note that it is possible for the LHS of (33) to be negative; for example, if demand for firm output is sufficiently inelastic, increasing productivity will cause the firm to tend to scale down input purchases.

overestimates the increase in total output, whenever the affected firm tends to increase inputs in response to increased productivity.

C.4 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.3, 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 $S_{j,t} \cdot \psi_t$. To account for these taxes and fees, we simply add ψ_t

to the marginal tax rate associated with firms' output. 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%].[37]

Combining these estimates, our final estimate of the effective tax rate facing firms is $(12.10\% + 5.77\%) = 17.87\%$

C.5 Complementary Evidence of Land Tax Yields

Figure A.4 plots the average VAT per square meter of industrial land by province (Panel (a)) and the minimum tax requirement by industry (Panel (b)).

C.6 Estimating Marginal Residential Tax Rates

Figure A.5 shows a scatter plot and binned scatter plot of the listed home developers' annual taxes and sales during 2007-2015.

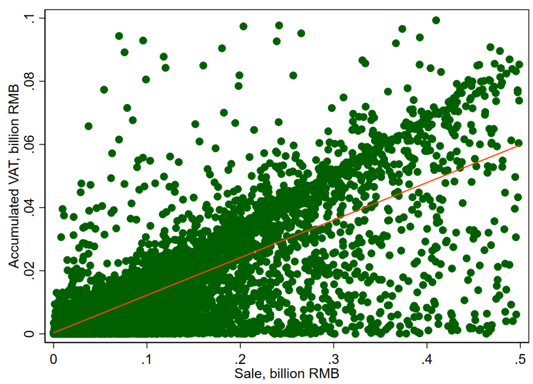
C.7 Classification of Targeted Industries

Table A.4 shows the list of industries that were ever targeted by one or both of the Five-year Plans initiated in 2006 and 2011.

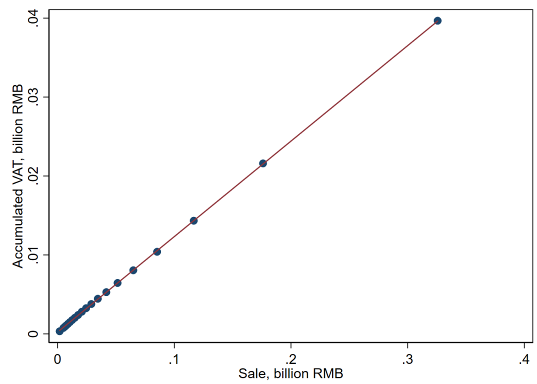
C.8 City Government Industrial Tax Share

In this section, we provide details on 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 C.4, 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

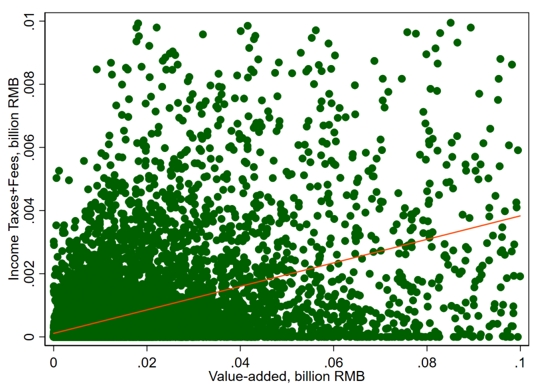
[37] Note that our estimate of income tax as a fraction of value-added is much lower than the official corporate income tax rate, which is 25%. This is because income taxes are applied to firm profits, which are a small fraction of value-added.



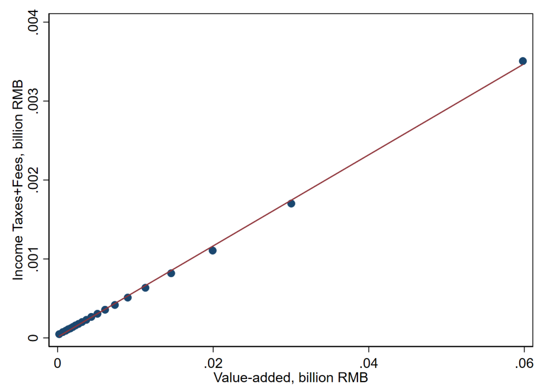
(a) Scatter Plot: Accu. VAT vs Sale



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



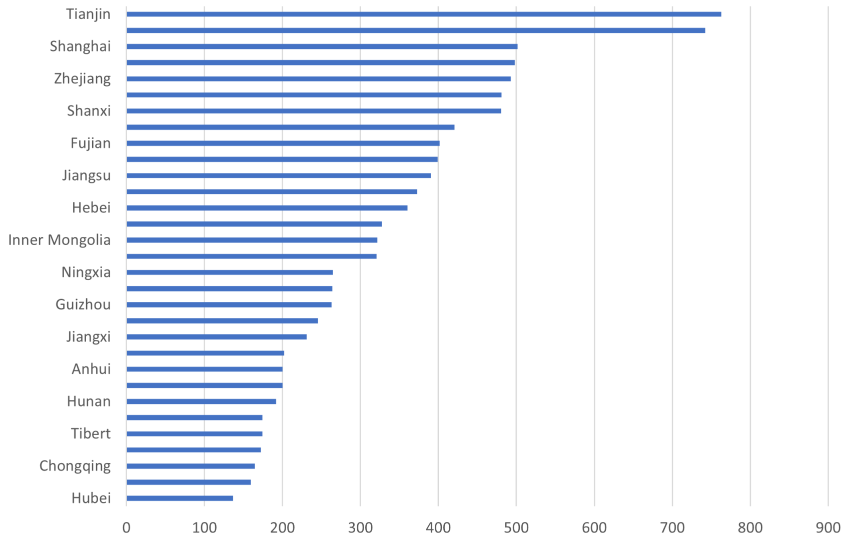
(c) Scatter Plot: Income Tax + Fees vs VA.



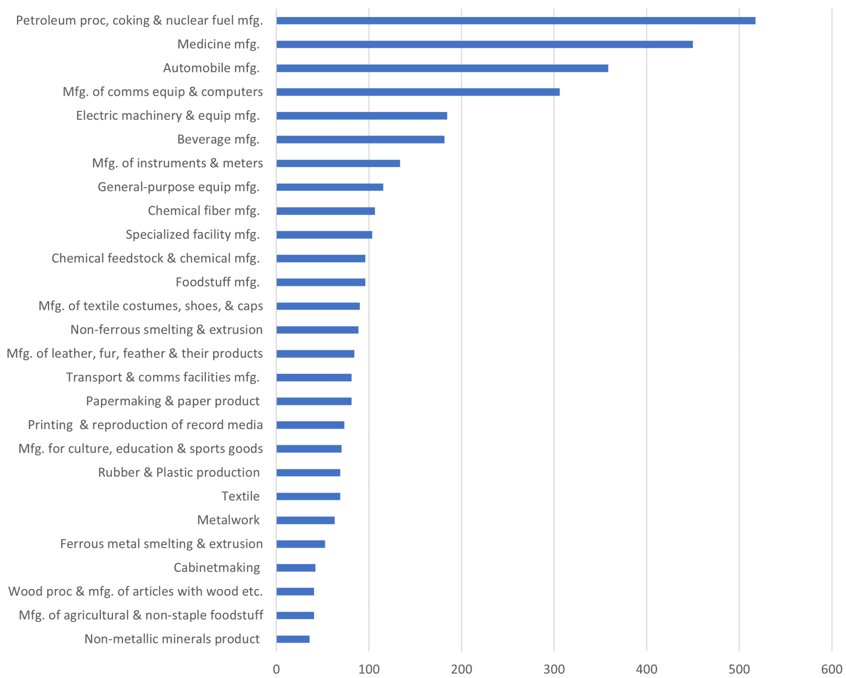
(d) Bin Scatter Plot: Income Tax + Fees vs VA.

Figure A.3: 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.



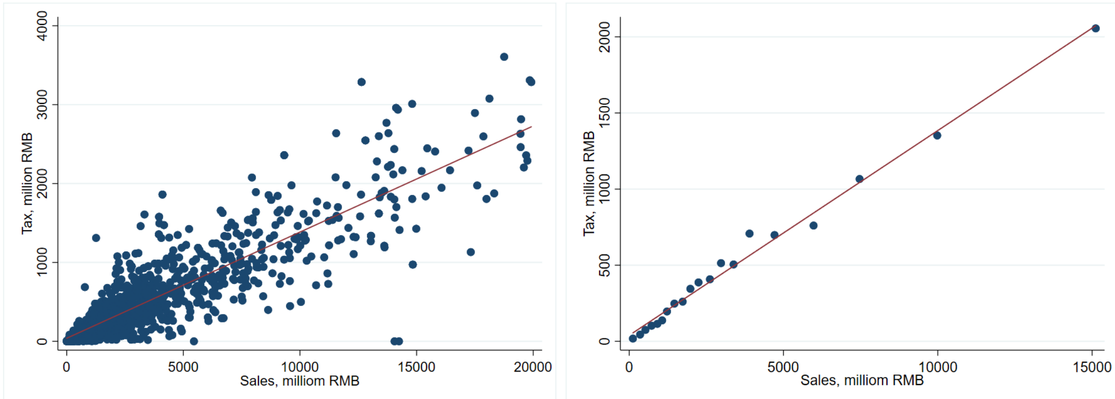
(a) Total VAT Over Industrial Land for Each Province, 2011, RMB/m^2



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

Figure A.4: Supplementary Evidence on Tax Income of Land

Notes: Panel (a) plots the total VAT paid by firms in each province divided by the stock of industrial land in that province in 2011. Panel (b) plots the industry-specific requirement on minimum tax payment by firms on industrial land set by Jiangsu Province in 2018 and Hunan Province in 2020. Values are in RMB/m^2.



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

Figure A.5: 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.

the city governments. Therefore, the city government share of industrial taxes is:

$$\mathrm{IndTaxShare}_c = \frac{12.10\% \times \mathrm{VATShare}_c + 3.33\% \times \mathrm{ITShare}_c + 2.44\%}{12.10\% + 3.33\% + 2.44\%} \tag{34}$$

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%.

D Supplementary Material for Section 5

D.1 Guangdong Policy Changes in 2016

The main policy change that most provinces made in 2016 was to change the share of VAT taxes accruing to city governments. However, Guangdong is an outlier: it did not change the city government VAT tax share, but implemented a number of other policies to encourage city governments to allocate more industrial land. These policies thus confound our analysis of the effect of VAT tax changes on industrial

Table A.4: 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.

land sales. When we include cities in Guangdong when estimating Equation (23), 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.5: 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.[38] 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.5: 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

D.2 City Govt Discount Rates, VAT Share and 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 discount rates and tax shares separately.

[38] 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.

D.2.1 City'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 the city governments, as follows:

$$CityDevTax_{c,t} = P^h_{c,t} \times FloorRatio_c \times CityDevTaxRate_{c,t}$$

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 $\mathtt{LateTerm}_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.2.2 Government Discount Rates and Developer Taxes

With the same specification as Eq. (22), we replace the dependent variable with the city's developer taxes $\mathtt{CityDevTax}_{ct}$. 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.

D.2.3 City VAT Share Changes and Developer Taxes.

With the same specification as Eq. (23), 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=	2011	-5.069	-27.97
		(-0.959)	(-0.382)
	2012	-1.723	-32.34
		(-0.360)	(-0.468)
	2013	0.804	-31.39
		(0.198)	(-0.518)
	2014	-5.003	-79.11
		(-1.333)	(-1.310)
	2016	2.669	-9.578
		(0.623)	(-0.163)
	2017	9.753*	88.04
		(1.664)	(1.537)
	2018	25.56***	187.9***
		(3.074)	(2.848)
	2019	7.140	201.4***
		(1.256)	(3.107)
Observations		2,081	2,090
R-squared		0.891	0.895
Year FE		Yes	Yes
City FE		Yes	Yes
#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 2011-2019, 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