

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

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Abstract

Public finance and real estate are uniquely intertwined in China, where local governments also serve as monopolist sellers of land. We shed new light on how land sale decisions and land prices depend on local governments' financing objectives. First, we document the large (ten-fold) price premium paid for residential-zoned relative to industrial-zoned land and show this price premium can be explained by the greater future tax revenues generated by industrial land; the choice to sell land as industrial rather than residential generates an IRR of 7.70%, which is comparable to local governments' cost of capital in bond markets. Second, local governments are sensitive to financing constraints: industrial land supply decreases with governments' bond yields. Third, local governments' land sales are sensitive to the intergovernmental tax sharing, such that industrial land sales increase with the share of taxes captured by local governments. Thus, shocks to local public finances can be expected to affect the Chinese real estate market and vice versa.

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

JEL classifications: H70, G31, R14, R38

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1 Introduction

China's real estate sector is intertwined with municipal government finances in an important way: Chinese city-level governments serve as monopolist sellers of land, and derive a large fraction of their operational revenues from land sales. Understanding the interactions between land markets and local public finance, which is often referred to as "land financing" (e.g., [Lin and Yi, 2011](#)), is thus important for understanding the Chinese economy more broadly.

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

This paper proposes an alternative explanation rooted in local public finance: rather than a trade-off between pecuniary and non-pecuniary benefits, we propose that local governments' choice between residential and industrial land sales reflects an intertemporal fiscal trade-off. Industrial land sales generate low sales revenues upfront, but industrial firms pay flow taxes in the future, which are captured by local governments. Residential land sales yield large up-front revenues for local governments, but generate no long-run revenues. We quantify the tax flows generated by industrial land sales, and show that they are large enough that the present value of industrial and residential land are similar, under reasonable discount rates. We provide causal evidence that shocks to local public finance affect land zoning decisions: when municipal bond rates increase or the city governments' share of industrial tax revenues decreases, local governments sell more residential land, which grants higher upfront revenues that all accrue to the city governments. Our results imply that land zoning decisions in China are intertwined with local governments' fiscal conditions, implying that shocks to local government finances thus potentially have knock-on effects on land supply.

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

To develop these results, we begin with some key institutional details. Land sales account for a substantial fraction of Chinese local governments' revenues. The central government imposes caps on the total amount of land that can be sold within a city, but city governments have large discretion on how to zone the land that they sell. Land use rights are sold to industrial firms to build factories, or residential land developers to build apartment building; the sales revenue from land accrues directly to local governments. The basic tradeoff local governments face is that residential land has higher upfront payments, but lower long-term revenues. In the process of residential land sales, governments do collect additional one-time tax revenues from residential land developers, as they build and sell apartments on residential land; however, there are no property taxes in China, so residential land sales generate no long-run revenues for local governments after apartments are built and sold. In contrast, while industrial land sells for much lower prices, industrial firms generate continuing tax revenue payments for local governments.

Building on these institutional details, we next develop a simple framework to analyze the determinants of local governments' land zoning decisions. Suppose a local government chooses land sales to maximize the present value of fiscal revenues; for simplicity, we ignore any non-pecuniary reasons for favoring one kind of land over the other. The local government should thus think of the decision to sell industrial land as akin to a firm's investment problem: selling a piece of industrial land is like investing in a project, where the upfront cost is the industrial discount – the gap between industrial and residential land prices – and the future payoffs are the higher taxes from industrial land relative to residential land. This analogy suggests a simple measure of the attractiveness of industrial land sales from a revenue perspective: the *internal rate of return* (IRR) on industrial land sales. When land sales have no price impact and city governments capture the entirety of industrial tax revenues, city governments optimally sell land until the industrial land IRR is equal to the governments' cost of capital. In practice, city governments share industrial tax revenues with the central government; in the presence of tax sharing, the city government sells somewhat more residential land and less industrial land, so the total IRR on industrial land should be somewhat higher than local governments' cost of capital.

We then attempt to empirically evaluate how industrial IRRs compare to governments' cost of capital. Measuring IRRs requires estimating 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 measure these quantities using 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.

We estimate the industrial discount based on a potential-outcomes framework. We use observed residential (industrial) sale prices to estimate a hedonic model to predict 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, we estimate that the average industrial land discount is 1012.83 RMB/m².

To estimate the marginal tax revenues from industrial land sales, we 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/m² in the first three years, and 214.2 RMB/m² thereafter.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 are fairly attractive to local governments, purely from a revenue standpoint.

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

²We also 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/m².

industrial IRR is roughly 3.80%, which is smaller than usual estimates of the government discount rate. We find that this decrease over time 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.

Our model also makes two other predictions about factors which influence industrial discounts and governments' zoning decisions. The first is specific to governments' cost of capital: when local governments are more financially constrained, they should sell more residential land, depressing residential prices and thus industrial discounts. A second prediction concerns the intergovernmental tax sharing: if local governments capture more of the tax revenues from industrial land sales, they will sell more industrial land, increasing industrial discounts.

We test and find support for both predictions. First, supporting our hypothesis about local governments' cost of capital, we show that industrial land discounts are negatively associated with local governments' cost of capital, as measured by local governments' municipal corporate bond yields, in the cross-section of cities. The negative correlation also holds when we instrument municipal corporate bond yields using an instrument that builds on [Chen et al. \(2020\)](#). Higher governments' cost of capital is also found to decrease industrial relative to residential land supply. Second, supporting our hypothesis about intergovernmental tax sharing, we find 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 experiencing a larger increase in their share of value-added taxes subsequently exhibited greater increases in industrial discounts and the difference between industrial and residential land supply.

The "land finance" system, through which land sales are a core source of local governments' revenues, is a relatively unique feature of public finance in the Chinese setting. Our results imply that this system causes land zoning decisions to be linked to the financial conditions and borrowing constraints of local governments. Shocks to land prices have the potential to impact local government revenues, and shocks to local governments' ability to raise financing in other sources can propagate into land markets through local governments' zoning decisions.

Moreover, outside the Chinese setting, the idea that land allocation decisions are intertwined with the revenue incentives of local governments has been studied in a number of other settings.³ Our result that land sale and zoning decisions are sensitive

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

to tax revenue sharing may hold in many settings outside China: for example, US city governments are largely funded by property taxes rather than local industrial taxes, and our results suggest that US city governments may be less than optimally supportive of industrial firm entry because they cannot capture the entirety of these firms' tax revenues, whereas changes in revenue sharing schemes may influence these choices. Moreover, although most studies based on the US have focused on the effect of municipal borrowing constraints on local policies in other aspects, our results imply a potential effect on the local land market also. Finally, our results have implications for settings where governments derive substantial revenues from the sales of other kinds of resources, such as mineral extraction rights, fishing rights, and radio spectrum.

Literature Review. Our paper is most related to the literature on financial decisions of local governments in different settings. Many papers have analyzed how the fiscal conditions of local governments and their debt-issuing capacities influence their expenditures, alternative sources of revenues, local policies and real outcomes. [Yi \(2021\)](#), [Posenau \(2021\)](#) and [Agrawal and Kim \(2021\)](#) show that credit-constrained municipalities cut spending, especially infrastructure investment and public facility expenditures, leading to deterioration of public service quality. [Zhang \(2021\)](#) shows that local governments' pension deficits can impact households' savings and investment in safe assets. [Giasecke and Mateen \(2022\)](#) show that local governments respond to negative fiscal shocks due to a large decline of property values by increasing property tax rates. [Adelino et al. \(2017\)](#) show that changes in local governments' financing costs can influence local governments' employment, as well as private sector employment and income. [Amornsiripanitch \(2022\)](#) analyzes how the decline of monoline insurance affects local governments' financing costs, expenditures, and public sector employment. [Pinardon-Touati \(2021\)](#) shows the crowding out effect of local government debt on corporate credit and investment in France. [LaPoint \(2022\)](#) analyzes sales of property tax-delinquent properties and the consequences on neighborhood composition and housing disparities in the US. A number of papers have investigated the consequences of pension underfunding in the US.⁴ Many more papers have studied the US municipal bond market.⁵

Among this literature, a few papers have also examined the interaction between local public finance and land regulations, particularly the fiscal incentives associated with different land use types ([Altshuler and Gomez-Ibanez, 2000](#); [Blöchliger et al., 2017](#)). For

⁴For example, see [Novy-Marx and Rauh \(2011, 2014\)](#). [Novy-Marx and Rauh \(2012\)](#) show that state pension fund losses are associated with municipal bond spreads. [Myers \(2019\)](#) shows how pension underfunding creates incentives for pensions to reach for yield. [Aiello et al. \(2021\)](#) analyzes how local governments' pension shortfalls affect local house prices.

⁵[Cestau et al. \(2019\)](#) provides a survey of this literature.

instance, [Quigley and Raphael \(2005\)](#) contend that tax policies in California create fiscal incentives to favor retail development over housing construction because property taxes are constitutionally limited while cities are permitted a share of local sales tax receipts. In Florida, [Burnes et al. \(2014\)](#) find that jurisdictions with higher sales tax rates prefer to attract large shopping malls over manufacturing firms through fiscal zoning. In the UK, [Cheshire and Hilber \(2008\)](#) investigate how the shift of tax revenues levied on commercial real estate from local authorities to the central government implies fiscal disincentives for commercial development, leading to high price for office space.

Our paper also relates to the literature on the Chinese land market. Several recent papers have examined the drivers of the gaps between industrial, residential, and commercial land prices in China. For example, [Xie et al. \(2019\)](#) examine the correlation between intergovernmental tax sharing and local governments' land allocation decisions using panel regressions. [Zhang et al. \(2022\)](#) put forth a similar viewpoint on the trade-off between up-front land revenue and future tax revenue in Chinese land market. Instead of comparing residential with industrial land, that paper compares residential with commercial land and more importantly, they focus on the relative supply without quantitatively comparing the tax difference to the upfront price gap.⁶ This paper adds to the literature by providing evidence from a more significant national market and highlighting the time dimension differences in fiscal revenues between residential and industrial land. [Liu and Xiong \(2020\)](#) 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. [Lei and Gong \(2014\)](#) argue that local governments distort prices of industrial land for non-pecuniary reasons relating to industrial agglomeration externalities, as well as for tax revenues. [Fan et al. \(2015\)](#) similarly model non-pecuniary reasons for low industrial land prices. A number of papers also analyze how corruption affects Chinese land prices ([Cai et al., 2013a](#); [Li, 2019](#); [Chen and Kung, 2019](#)).⁷ [Tian et al. \(2022\)](#) analyze how the design of land auctions affects the efficiency of land allocation in China. While we may refute some explanations, our perspective is largely complementary to these alternative views.

Our paper also relates to a small literature on the land market in the US. [Nathanson and Zwick \(2018\)](#) analyze land speculation by US property developers.

⁶Residential land prices were about 10 times higher than industrial land prices from 2007 to 2019. In contrast, residential land prices were similar to commercial land prices prior to 2014, but by 2019 they had roughly doubled.

⁷Other papers on Chinese land markets include [Tan et al. \(2020\)](#), [Deng et al. \(2020\)](#), [Fu et al. \(2021\)](#), and [Henderson et al. \(2022\)](#).

2 Data and Institutional Details

This section provides a brief summary of the key institutional background for Chinese land markets, followed by the description of data used in this paper.

2.1 Institutional Background

Local government financing. Unlike countries such as the US, where land transactions are typically conducted directly between private parties, the majority of land transactions in China are intermediated by local governments. Specifically, local governments frequently repossess “underutilized” land, compensating any existing occupants of the land, and then resell the land to market participants such as manufacturers and home developers using auction-like mechanisms. Land transfers that are not intermediated by local governments do occur, but are fairly limited in scope. Economically, this process allows local governments to upgrade decaying public infrastructure, encourage building higher and more efficient structures on land, and change zoning to reallocate land to different use cases.

Besides its role in increasing the efficiency of land utilization, the requisition and resale of land is a highly profitable activity, accounting for approximately a third of local governments’ revenues.⁸ The large role that land sales play in Chinese local public finance is often referred to as the “land finance” system. For example, a group of well-known Chinese scholars and policy makers (Cai et al., 2013b) write: “Land finance is a key challenge: most Chinese cities fund their urban infrastructure largely from land sales... land sale revenue accounts for about one third of total local government revenue during 2010-2012.”

In addition to direct land-sale revenues, land sales also generate tax revenues. The nature of the tax revenue depends on how the land is zoned. When the land is sold for residential use, tax revenue from the land is typically a one-time event: developers build and sell apartment units, a process subject to business taxes that we analyze in Subsection 4.3, but all future use and resale of this housing is not taxed in China. In contrast, when land is sold for industrial use, the land typically generates an ongoing stream of future tax revenue: factories built on the land subsequently pay taxes annually. Hence, residential land sales generate relatively front-loaded revenue for local governments, whereas industrial land sales generate a relatively back-loaded stream of future revenue.

⁸In 2019, local governments’ fiscal revenue primarily came from three sources: 10 trillion RMB from general revenue, 7.5 trillion RMB from the central government transfer payments, and 7.3 trillion RMB from land sales.

Residential and industrial land sales also differ in the intergovernmental sharing of revenues. Tax revenues are divided between central and local governments, whereas the direct proceeds from the land sale accrue entirely to local governments.

Land quota system and land allocation. In China, central governments largely determine the total amount of land supplied, but local governments have substantial discretion over how land is zoned for sale. The urban landscape is mostly regulated by two laws: the [Land Administration Law](#) and the [Urban and Rural Planning Law](#). The two laws regulate the division between urban and rural land and the spatial layout of urban and rural areas. During our sample period, they were enforced through the “Land Use Overall Plans” implemented at all levels of governments and the “Urban Overall Plans” at the city and subordinate county and town level.⁹ In general, the first set of plans lists regulations about the scale of the cities, and the second gives more details on land zoning. In drafting these plans, the upper-level governments (central and provincial) lay out planning guidelines that include caps on the scale of the cities, and lower-level governments (city and subordinate county and town) are in charge of specifying land zoning at detailed areas until parcel level.¹⁰ Although lower-level plans are always subject to the review of upper-level governments, the choice of how to zone them for different uses is largely in the hands of local governments, especially in the short run.

The land usage permitted for each land parcel, falls into four categories: residential land for housing construction, industrial land for the construction of factories and warehouses, commercial land for offices and shopping malls, and public utility land for public facilities including schools and hospitals. In this study, we will focus on residential and industrial land, which accounts for 86% of the total land supplied in terms of area between 2007 and 2019.

⁹The two plans, along with some other related plans, were combined into a single Territorial Spatial Plan since 2019. See [here](#).

¹⁰In implementing the “Urban Overall Plans” or 城市总体规划 in Chinese, the Ministry of Housing and Urban-Rural Development in the central government publishes guidelines on the split of land use types. For example, the [2012 Code for Classification of Urban Land Use and Planning Standards of Development Land](#) states that residential land share should fall between 25% and 40% and the industrial land share between 15% and 30%, leaving city governments quite discretion within these bounds. Moreover, these bounds do not seem to be strictly enforced in practice. Based on the Urban Construction Statistic Yearbook, we calculate that during 2007-2019, the industrial land share bounds were violated by 42% and the residential land share bounds were violated by 26% of city-by-year observations.

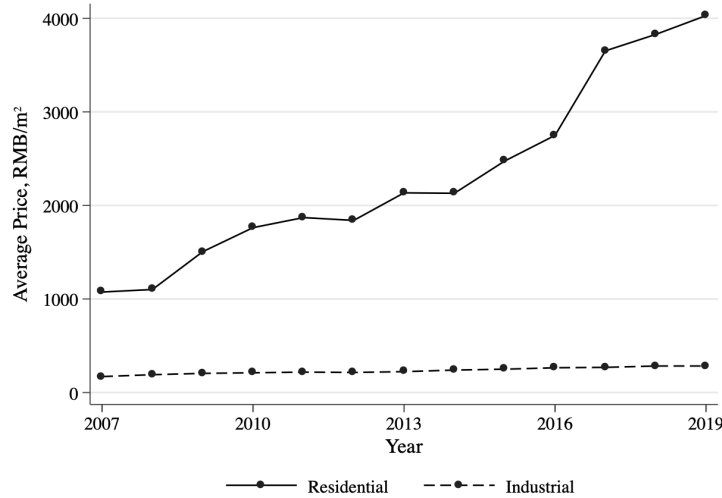


Figure 1: Average Land Prices Over Time by Land Use: Industrial vs. Residential

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. For each land transaction, we observe the land geographic location, size, transaction date, price and designated use type. We focus on residential and industrial land parcels allocated by agreement, tender, auction and listing.¹¹ 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 provider in China.¹² 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 National Bureau of Statistics on all industrial (manufacturing, mining, and utility) firms in China during 1998-2013. For each firm, we observe detail information such as firm name, industry, annual sales, profits and tax payment. Despite some concerns about

¹¹We exclude an allocation mechanism called “administrative allotments” involving no payment from land receivers, which is used for infrastructure, government offices, military facilities, etc.

¹²See <https://lbs.amap.com/>.

the data quality (Nie et al., 2012), the data has been widely used in economic research on China.¹³ Besides the issue of missing 2010 data,¹⁴ it is also subject to censoring and random dropout concerns, which we analyze in appendices A.1 and C.4.

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

Summary statistics of our data are shown in Table 1.

3 Conceptual Framework

We start with defining the industrial land discount and the government's IRR on industrial land sales. We then construct a simple conceptual framework in which an optimizing local government decides how much industrial versus residential land to sell, which

¹³Some 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).

¹⁴For 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 City 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.

allows us to illustrate the forces that should drive empirically measured IRRs to vary.

3.1 Industrial Land Discounts

Figure 1 shows a striking stylized fact: 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 revenue-maximizing local governments did not reallocate land from industrial to residential uses, until the point where the prices in the two markets are equal. Conceptually, we will use “industrial discounts” to refer to the difference in upfront sales revenues received by the government from selling industrial versus residential land. Suppose a single parcel of land is sold, and the price is expected to be p_t^{ind} if it is sold as industrial and p_t^{res} if it is sold as residential land. We define the industrial discount as:

$$\text{IndDisc}_t \equiv p_t^{\text{res}} - p_t^{\text{ind}} - \lambda p_t^{\text{res}} \quad (1)$$

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

There are essentially three kinds of costs that local governments incur in the process of taking land for resale from incumbent landowners. First, governments need to pay a fixed “standard” compensation amount to incumbent land occupants to repossess land for resale; these costs apply equally to both kinds of land, so we will ignore them in computing industrial discounts. Second, there is a variable component of compensation to incumbent landholders, which depends on the sale price of the repurposed land: since residential land is more expensive, governments will pass on some of these higher revenues to incumbent landholders. Third, when local governments sell residential land, they often have to allocate extra land and revenue for supportive functions, such as education, associated with new residences. The latter two forces imply that the total costs of selling residential land are somewhat higher than the costs of industrial land. In Appendix C.1, using aggregate data on compensation to incumbent landowners and land provided for public services, we estimate that the sum of these two variable costs is about 1/3 of residential sale revenues. Hence, we set $\lambda = 1/3$ in (1).

3.2 Tax Revenues and the IRR on Industrial Land Sales

While industrial land sales generate less upfront sale revenues than residential land sales, we will show that industrial land generates higher long-run tax revenue flows. We

can thus think of the government's land zoning decision as akin to a firm's investment problem: selling a piece of industrial land is like investing in a project, where the upfront cost is the industrial discount, and the payoff is the long-run difference in tax revenues between industrial and residential land. Building on this analogy, we will measure the attractiveness of industrial land sales as an internal rate of return, IRR^{ind} . 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.

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:

$$IRR_t^{ind} \equiv \left\{ \rho : \underbrace{\sum_{s \geq t+1} \frac{Tax_{t,s}^{ind}}{(1+\rho)^{s-t}}}_{PV(\text{tax}^{ind})} + \underbrace{\sum_{s \geq t+1} \frac{Tax_{t,s}^{res}}{(1+\rho)^{s-t}}}_{PV(\text{tax}^{res})} = \underbrace{(1-\lambda)p_t^{res} - p_t^{ind}}_{IndDisc} \right\} \quad (2)$$

The RHS of (2) is the industrial land discount, as defined in (1). On the left hand side, $Tax_{t,s}^{ind}$ is industrial taxes per square meter of land in year s due to firms' land purchase in year t , and $Tax_{t,s}^{res}$ is residential taxes per square meter of land in year s due to home developers' land purchase in year t . We will assume that tax cash flows start to accrue one year after the land purchase.

3.3 A Conceptual Framework for Drivers of IRR^{ind}

We now describe a simple conceptual framework to illustrate the forces that would affect IRR^{ind} . We describe the model setup and results in the main text; the formal model is in Appendix B.

In the model, a local government allocates a fixed amount of land inventory between industrial and residential land. Industrial land generates persistent cash flows in the form of firm tax payment while residential land does not. The city government aims to maximize the present value of all revenues from land sales. We assume that all land sale revenues accrue to the city government, but the city government may not internalize all the tax revenues from industrial land, since some fraction of these taxes is captured by the upper-level government.¹⁵ Within the model, we can solve for the equilibrium IRR on industrial land sales.

¹⁵In Section C.10 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%.

If land demand is perfectly elastic and city governments capture the entirety of tax revenues from industrial land, a city government's optimality condition is identical to that of a firm making investment: city governments sell industrial land until the marginal tax payment from industrial land reaches the point such that the IRR on industrial land is equal to the government's cost of capital, $IRR^{ind} = r^{gov}$. More patient governments, with lower costs of capital r^{gov} , will tend to sell more industrial land.

Suppose, however, that the city government only internalizes a share $k \in (0, 1)$ of tax revenues from industrial firms. Here, k corresponds to the share of taxes that directly accrue to city governments if they are deciding land allocations solely, but more broadly can be thought of as the eventual weight that the bargaining outcome places on tax revenue when city governments negotiate with higher-level governments over land allocations. We then have:

$$IRR^{ind} = \frac{r^{gov}}{k}. \quad (3)$$

When $k < 1$, we will have $IRR^{ind} > r^{gov}$. Intuitively, when local governments capture only a fraction of tax revenues, IRRs will tend to be higher – industrial land will appear to be an attractive investment, but local governments will not invest because they do not receive the entirety of the output from their investments. This framework thus predicts that IRRs should be higher when local governments' cost of capital is higher, and when local governments internalize a smaller fraction of industrial tax revenues. We will test both predictions empirically in Section 5.

How would the land demand elasticities play a role in this context? Local governments are monopolistic sellers of land in the local market. When selling residential land, they will take into account the negative price impact and maintain a high residential land price, which can partially explain the existence of the industrial land discount. Importantly, our estimation in this paper will show the quantitative importance of tax revenues relative to the observed industrial discount (as evidenced by a high IRR^{ind}), even if we do not deduct the effect of market power from the observed industrial discount. In other words, future tax revenues will be quantitatively more important when compared to the residual of industrial discount not explained by market power.

We stress that, in this framework and throughout the paper, we ignore all potential non-pecuniary benefits or costs that the government derives from choosing industrial rather than residential zoning. This is not because we believe these non-pecuniary benefits do not exist: rather, our goal is to ask whether revenue concerns alone are sufficient to explain the gap between the prices of industrial and residential land.

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; $\text{Tax}_{t,s}^{\text{ind}}$, the stream of future tax revenues generated by industrial land sales at t ; and $\text{Tax}_{t,s}^{\text{res}}$, the stream of taxes paid by home developers when they build and sell houses. We estimate industrial discounts in Subsection 4.1, industrial tax revenues in Subsection 4.2, and developer tax revenues in Subsection 4.3. We combine these estimates and calculate IRRs in Subsection 4.4.

4.1 Industrial Discount Estimation

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

$$p_{i,t} = p_{i,t}^{\text{res}} \times \mathbf{1}_{i,t}^{\text{res}} + p_{i,t}^{\text{ind}} \times (1 - \mathbf{1}_{i,t}^{\text{res}}) \quad (4)$$

Our goal is to estimate both outcomes $p_{i,t}^{\text{res}}$ and $p_{i,t}^{\text{ind}}$, only one of which is observed.

The main challenge is that land parcels are not randomly zoned and it is likely that $\mathbb{E}[p_{i,t}^{\text{res}} | \mathbf{1}_{i,t}^{\text{res}} = 1] \neq \mathbb{E}[p_{i,t}^{\text{res}} | \mathbf{1}_{i,t}^{\text{res}} = 0]$ and $\mathbb{E}[p_{i,t}^{\text{ind}} | \mathbf{1}_{i,t}^{\text{res}} = 1] \neq \mathbb{E}[p_{i,t}^{\text{ind}} | \mathbf{1}_{i,t}^{\text{res}} = 0]$. 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{J}_{res} and \mathcal{J}_{ind} represent the sets of parcels observed to be residential and industrial, respectively:

$$\mathcal{J}_{\text{res}} \equiv \{i : \mathbf{1}_{i,t}^{\text{res}} = 1\}, \mathcal{J}_{\text{ind}} \equiv \{i : \mathbf{1}_{i,t}^{\text{res}} = 0\}.$$

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

$$p_{i,t} = X_{i,t} \cdot \beta^{\text{res}} + \gamma_{u,t}^{\text{res}} + \epsilon_{i,t}, \quad \forall i \in \mathcal{J}_{\text{res}}. \quad (5)$$

Eq. (5) is a standard hedonic model that predicts $p_{i,t}$, the price per square meter of each residential land parcel (Wu et al., 2014; Chen et al., 2017). To control for the price impact of local economic conditions such as economic development, local land market corruption and any other local price distortions, we construct very granular “urban units,” which are contiguous urban clusters as identified by satellite images (see Appendix A.2) with average size of 20 square kilometers. We then match each land parcel to the closest urban unit and include urban-unit-by-year fixed effects $\gamma_{u,t}^{\text{res}}$.¹⁶ 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. (5) by restricting the sample to the set of land parcels sold by auctions. To account for the possibility that the coefficients may vary over time and across cities, we estimate (5) separately for each prefecture city, and separately for two time periods: 2007-2010 and 2011-2019. Since specification (5) 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 (5), we can then predict residential prices for industrial parcels by plugging characteristics of these parcels into Eq. (5):

$$\hat{p}_{i,t}^{\text{res}} = X_{i,t} \hat{\beta}^{\text{res}} + \hat{\gamma}_{u,t}^{\text{res}}, \quad \forall i \in \mathcal{J}_{\text{ind}}. \quad (6)$$

That is, $\hat{p}_{i,t}^{\text{res}}$ is the predicted price of parcel i if it were sold as residential land. Analogously, we fit a hedonic model to industrial land parcels, with the same control variables as in (5):

$$p_{i,t} = X_{i,t} \beta^{\text{ind}} + \gamma_{u,t}^{\text{ind}} + \epsilon_{i,t}, \quad \forall i \in \mathcal{J}_{\text{ind}}. \quad (7)$$

¹⁶We 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.

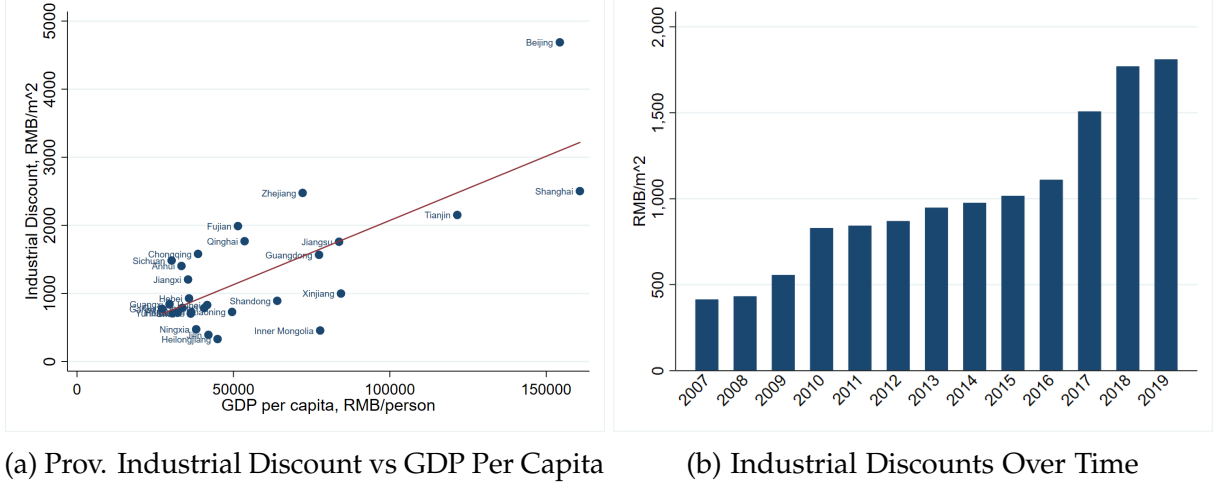


Figure 2: Industrial Discount Estimates Summary.

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.

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

$$\hat{p}_{i,t}^{\text{ind}} = X_{i,t} \hat{\beta}^{\text{ind}} + \hat{\gamma}_{u,t}^{\text{ind}}, \quad \forall i \in \mathcal{J}_{\text{res}}. \quad (8)$$

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

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

In words, $\text{IndDisc}_{i,t}$ 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 $\text{IndDisc}_{i,t}$ at the land parcel level. We then aggregate to form city-year level estimates, $\text{IndDisc}_{c,t}$, by taking averages of $\text{IndDisc}_{i,t}$ 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/m² during 2007-2009 and increased to 750 RMB/m² 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/m², four

times the level in 2007.¹⁷

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

Second, our methodology may be confounded by unobserved differences between industrial and residential parcels, which could cause counterfactual prices of land parcels to be systematically different from what our pricing models predict. Importantly, the existence of such unobservable characteristics, if any, is most likely to generate upward bias to the industrial land discount estimates, as land parcels with better unobservable quality tend to be zoned as residential. This potentially strengthens our key take-away that future industrial tax revenues are quantitatively important relative to the upfront industrial land discount.¹⁸

Third, the magnitude of the bias due to unobserved factors is unlikely to be quantitatively large. Although the features of land parcels used in our pricing models, i.e., Equation (5) and (7), explain 50% of the variation in land prices, controlling for observable characteristics only changes average industrial discounts by around 10%. Hence, selection on observable characteristics has a relatively small effect on estimated industrial discounts. Any unobservable characteristics that can substantially affect our results would need to be both important drivers of house prices and highly correlated with the observable characteristics of industrial versus residential land parcels, as argued by Oster (2019).

One particular unobserved variable which is known to be an important driver of land prices is corruption (Li, 2019; Chen and Kung, 2019). Our procedure does not require the absence of corruption in the land market but assumes the corruption is not different between observed and counterfactual residential land sales. For example, if half of observed residential land sales are corrupt and corruption lowers prices by 20%,

¹⁷From 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.

¹⁸Controlling for land heterogeneity $X_{i,t}$ in Equation (5) and (7) reduces the industrial discount estimates by roughly 8%.

our estimates remain valid if counterfactual residential land sales have similar levels of corruption and price reduction. There is no particular reason to believe the extent of corruption would be different on the industrial land parcels if they were zoned as residential, since corruption is a city-level rather than land parcel-level phenomenon.

Finally, our baseline estimates use the *average* industrial discount, over all land parcels in a given city-year, as input. In Appendix section C.3, we explore whether the estimates are different using the *marginal* land parcels whose use would be adjusted if the government wanted to adjust the land allocation between residential and industrial use on the margin. Using a simple discrete-choice model of land use decisions which perform reasonably well in predicting land uses, we estimate the distribution of marginal land parcels and find that the industrial discount estimates based on marginal land parcels are very similar to those in our baseline specification, differing by only 1.5%-2.5% quantitatively.

4.2 Industrial Tax Estimation

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

4.2.1 The Effect of Land Purchase on Sales

We essentially measure the effect of purchasing a square meter of industrial land on firms' sales revenue by comparing the sales growth of firms after they purchase land, to control firms matched on characteristics who do not purchase land.

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

$$S_{j,t} = \begin{cases} \alpha_j + \eta_t + \varepsilon_{j,t} & t < \tau_j \\ \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \Delta_j + \varepsilon_{j,t} & t \geq \tau_j \end{cases} \quad (9)$$

In words, Eq. (9) states that firms' sales are determined by time-varying factors η_t , time-invariant firm-specific factors α_j , and land purchases Δ_j , whose effect depends on a parameter $\theta_{t-\tau_j+1}$. 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 $2007 \leq \tau_j \leq 2013$. For cleaner identification, we focus on the sample of firms who have purchased land only in one year in our sample period.¹⁹ In contrast, control firms are those that never acquired any industrial land during the sample period (so that $\tau_j = \infty$), regardless of the transfer method.

A natural concern with estimating the parameters $\theta_{t-\tau_j+1}$ in Eq. (9) is that land purchasing firms are different from non-purchasers: in other words, land purchase decisions may be correlated with firm-time-specific shocks $\varepsilon_{j,t}$. To address this concern, we decompose these shocks as

$$\varepsilon_{j,t} = f_t(p(x_{j,\tau_j-1})) + e_{j,t}. \quad (10)$$

In this decomposition, f_t can be any function, and $p(x_{j,\tau_j-1})$ is a firm's probability of purchasing land given observables x_{j,τ_j-1} . We make the identifying assumptions:

$$\mathbb{E}[e_{j,t}\Delta_j \mid \alpha_j, \eta_t, \tau_j \in \{\tau, \infty\}] = 0 \quad \text{and} \quad \mathbb{E}[e_{j,t}\mathbf{1}_{\Delta_j > 0} \mid \alpha_j, \eta_t, \tau_j \in \{\tau, \infty\}] = 0, \quad \forall \tau \quad (11)$$

In words, the two requirements for $e_{j,t}$ are that shocks to firm sales are uncorrelated with (i) the amount of land purchased and (ii) the decision 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 are *unrelated* to the probability of land purchase predicted by x_{j,τ_j-1} (see Eq. (10)), 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 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 $\hat{p}(x_{j,\tau_j-1})$ based on the three following observables at the firm level:

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

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

Here, $S_{j,t}$ is firm j 's sales in period t and $\text{Profit}_{j,t}/S_{j,t}$ is firm j 's profit margin in period t . In our data, we find these three variables are predictive of land purchase decisions. Following the suggestions by the literature (Dehejia and Wahba, 1999; Blundell and Costa Dias, 2000; Smith and Todd, 2005), we match firms based on two years of pre-treatment sales data, which are viewed as important to deliver robust and consistent estimates of the treatment effect.

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

$$\bar{\Delta}_\tau \equiv \mathbb{E} [\Delta_j \mid \Delta_j > 0, \tau_j = \tau], \quad (12)$$

which essentially estimates the average land size at a particular year τ by averaging over land transactions in that year. Using Eq. (9), firm sales can be written as

$$S_{j,t} = \alpha_j + \eta_t + \theta_{t-\tau_j+1} \cdot \mathbf{1}_{\Delta_j > 0} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}, \quad (13)$$

where we define

$$\varepsilon'_{j,t} \equiv \begin{cases} \varepsilon_{j,t}, & \Delta_{j,t} = 0; \\ \varepsilon_{j,t} + \theta_{t-\tau_j+1} \cdot (\Delta_{j,t} - \bar{\Delta}_{\tau_j}), & \Delta_{j,t} > 0. \end{cases} \quad (14)$$

Note that,

$$\mathbb{E}[\varepsilon'_{j,t} \bar{\Delta}_{\tau_j} \mid \alpha_j, \eta_t] = 0, \quad (15)$$

where we use conditioning on α_j and η_t to reflect controlling for firm and time fixed effects. This follows from (11) thanks to the definition of $\bar{\Delta}_{\tau_j}$ in Eq. (12). In light of Eq. (15), we can consistently estimate $\theta_{t-\tau_i+1}$ with difference-in-differences estimation using regression specification (13).

Results. Table 2 reports the estimates of specification (13). 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

Table 2: Dynamic Treatment Effect of Land Purchase on Sales

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

Note: This table reports estimation results of Model (13) with the matched sample. We drop the matched pairs whenever the treated or the control firm exits the sample. For each treatment year $\tau \in \{2007, 2008, \dots, 2010\}$, 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 m². The year of $t = \tau - 1$ is used as the base year. Standard errors are clustered by firms. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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

Third, and importantly for validating our matched difference-in-differences identifi-

Table 3: Baseline Estimation of Marginal Output of Land

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

Note: This table reports estimation results of Model (16) 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 $\tau \in \{2007, 2008, \dots, 2010\}$, 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 1,000m². Standard errors are clustered by firms. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

cation assumptions, treated and control firms are not significantly distinguishable prior to land purchase. Note that our matching procedure guarantees that the parallel trend holds between the treated and control firms from $t = \tau - 2$ to $t = \tau - 1$, but not before. The fact that the parallel trend additionally holds from $t = \tau - 4$ to $t = \tau - 2$ lends some support to our identification assumption.

Motivated by these patterns, Table 3 summarizes the estimated treatment effects more concisely. 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. To circumvent the potential issues due to staggered treatment in the pooled regression (De Chaisemartin and d’Haultfoeuille, 2020; Baker et al., 2022), we use the stacked DID by allowing treatment-specific time-fixed effect

(Cengiz et al., 2019; Deshpande and Li, 2019). Formally, we estimate

$$S_{j,t} = \alpha_j + \eta_{t,\tau_j} + \theta_{\text{short}} \cdot \mathbf{1}_{\Delta_j > 0, t - \tau_j \in \{0,1,2\}} \cdot \bar{\Delta}_{\tau_j} + \theta_{\text{long}} \cdot \mathbf{1}_{\Delta_j > 0, t - \tau_j > 2} \cdot \bar{\Delta}_{\tau_j} + \varepsilon'_{j,t}. \quad (16)$$

In Equation (16), the subscript τ is the event year for the treated and the matched control firms. It is stacked DID as the time fixed effect varies with τ .

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, in the first three years after land purchase, land sales generate an additional 636.2 RMB/m² in sales on average per year; and in subsequent years after land purchase, land sales generate a long-run effect of 1199 RMB/m² in sales on average per year.²⁰

An issue commonly associated with the PS-DID method is that the identification assumption could fail if treated firms acquire new land in response to an unobserved positive shock in the same year when they are impacted by the shock, despite displaying similar behavior to matched control firms prior to the land acquisition. However, we contend that this is unlikely. In reality, when impacted by an unexpected positive shock, firms will first choose on-site plant expansion as the primary means of increasing production capacity. Only when they experience significant diseconomies associated with on-site expansion will they consider establishing new plants, which necessitates thorough market research and site selection (Schmenner, 2005). Thus, it seems improbable that firms could acquire new land within the same year of being hit by a positive shock.

We conduct one test to support our argument. If firms can respond within the same year as the positive shock, then land purchases made in the second half of the year would likely be a result of the shock, while purchases made in the first half of the year would be more likely due to a positive shock from the previous year. Thus, when matching firms based on previous characteristics, the potential positive bias from the matched sample would be greater for firms that bought land in the second half of the year. However, Table 3 Column (2) does not support this prediction, where we interact the treatment effect with a dummy H2 which equals 1 for firms that bought land in the second half of the year and 0 otherwise. The treatment effect is similar, regardless of whether the firm purchased the land in the first or second half of the year.

Before leaving this section we discuss one econometric issue regarding panel imbalance.

²⁰As 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 .

Firms enter and exit our panel due to data linkage issues. 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.4 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.4 makes our estimates of land-purchase treatment effects conservative.

4.2.2 Firm Tax Estimation

We now calculate the marginal tax revenues generated by firms' land purchases. The most important taxes paid by industrial firms are value-added taxes and corporate income taxes, with both being approximately linear functions of the firm's value added.²¹ 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.5 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 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.

What remains is to estimate effective tax rates. We do this in Appendix C.6, essentially

²¹For a detailed description of the system of firm taxation in China, see Appendix C.6.

by regressing accumulated VAT from firms on their sales. As shown in Figure A.5, averaging across firms, we see a strikingly linear relationship: the average value-added tax rate, which is approximately 12.10%, is very stable on average across firms of different sizes, though for any given firm size there is some variation in effective tax rates. 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%.²²

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

$$\text{Tax}_{t-1,s}^{\text{ind}} = 636.2 \times 17.87\% = 113.6 \text{ RMB/m}^2, \text{ for } s - t \in \{0, 1, 2\} \quad (17)$$

$$\text{Tax}_{t-1,s}^{\text{ind}} = 1199 \times 17.87\% = 214.2 \text{ RMB/m}^2, \text{ for } s - t > 2 \quad (18)$$

4.2.3 Complementary Evidence

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

Average VAT income from industrial land. As a first benchmark, we compare our estimated marginal effect of land sales on 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,²³ divided by total industrial land size (from China City Construction Yearbook). Appendix Figure A.6a 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/m². 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/m² in Eq. (18).

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

²²The tax rates are estimated using data during 1998-2012, with barely variation over time.

²³We 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.

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).²⁴ 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.6b plots the industry-specific minimum requirement on annual tax payments set by Jiangsu and Hunan province for manufacturing industries. The minimum tax requirement for most industries is around 100 RMB/m². 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/m². We thus conclude our marginal tax estimate of 214.2 RMB/m² 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 which residential land sales increase tax revenues. 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 $\text{Tax}_{t,s}^{\text{res}} = \mathbf{1}_{s=t+1} \times \text{DevTax}_s$ with DevTax_s denoting the developer taxes per square meter of residential land in year s .²⁵

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

$$\text{DevTax}_{t,c} = P_{t,c}^h \times \text{FloorRatio}_c \times \text{DevTaxRate}_t, \quad (19)$$

²⁴Other 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.

²⁵In 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.

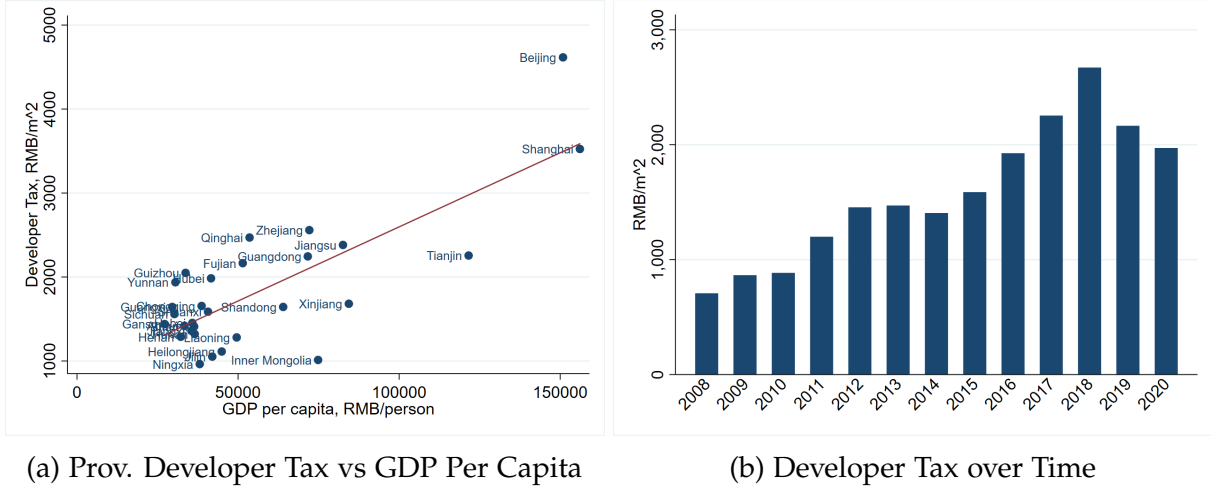


Figure 3: Developer Tax Estimates Summary.

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.

where $P_{t,c}^h$ is the average house price per square meter of livable space; $FloorRatio_c$ is the average amount of livable space that is built per square meter of residential land; and $DevTaxRate_t$ is the expected amount of taxes developers pay, for each RMB increase in their total sales in year t .

We calculate $P_{t,c}^h$ using total house sale revenues divided by the total construction area of houses sold in city c and year t . We measure $FloorRatio_c$ 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 $DevTaxRate_t$, we use data of listed developers in year t and regress the firms' total annual taxes on annual sales.²⁶ Appendix Figure A.7 shows the relationship between the listed developers' annual taxes against their sales. The relationship is close to linear year by year, suggesting that $DevTaxRate_t$ 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.

²⁶Since 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.

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. (2). 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 fourth 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.

4.4 IRR^{ind} Estimates

In this section, we use the framework of Section 3 to calculate 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 $\text{IndDisc}_{c,t}$ during 2007-2010 and $\text{DevTax}_{t,c}$ 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/m², and the weighted-average developer taxes during 2008-2011 is 1453.03 RMB/m². Combining this with the estimates of industrial tax revenues, which are 113.6 RMB/m² in the first two years given by Eq. (17) and 214.2 RMB/m² thereafter given by Eq. (18), we calculate the government IRR in Eq. (2) to be $\text{IRR}^{\text{ind}} = 7.70\%$.

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 the provincial and the city level.²⁷ 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.²⁸

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%. In other words, industrial land appears to be a profitable investment given city governments' costs of capital: if a city government borrowed using MCBs at r^{gov} , and used this revenue to sell industrial land rather than residential land and make IRR^{ind} , the city would make positive profits on average. At the low end of MCB yields, industrial land appears like a very profitable investment; this raises the question why city governments do not sell more industrial land, until the point where IRR^{ind} decreases to be equal to r^{gov} . One possible explanation, which we will explore further in Subsection 5.2, is that local governments only capture a fraction of the tax revenues generated by industrial land sales, so that their perceived return on investment is lower than our measured IRR^{ind} .

In sum, guided by the simple economic framework developed in Section 3.2, our estimated IRR^{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

²⁷As 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).

²⁸We 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.

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 IRR^{ind} .

First, we calculate IRR^{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)).²⁹ This addresses concerns that the government may be subsidizing targeted industries through other favorable policies, causing IRR^{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 IRR^{ind} for targeted industries to be 8.05% (unreported), which is 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/m², 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

²⁹Table C.9 in the appendix shows the list of targeted industries.

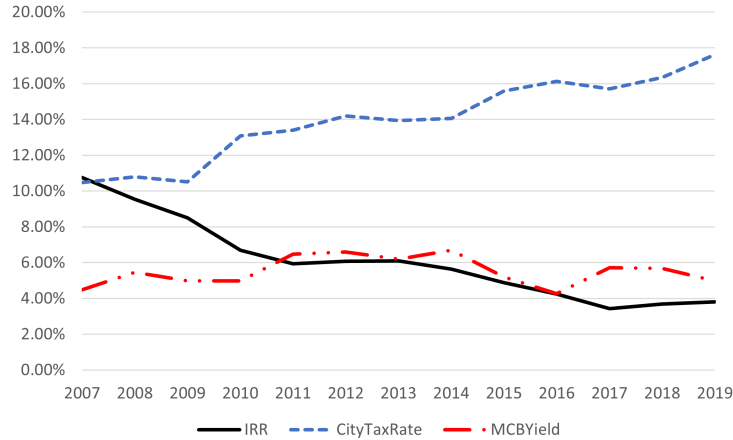


Figure 4: Industrial Discount and IRR

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. (17) and (18) 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.

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.

As implied by Eq. (3) 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.³⁰

³⁰If we replace the total tax measures in Equation (2) with the amount of tax that goes to the city government based on their annual tax share, the IRR will be more stable over time, i.e., it will only decrease by 2.8% from 2007 to 2019 as compared to a decrease of 6.9% in Figure 4.

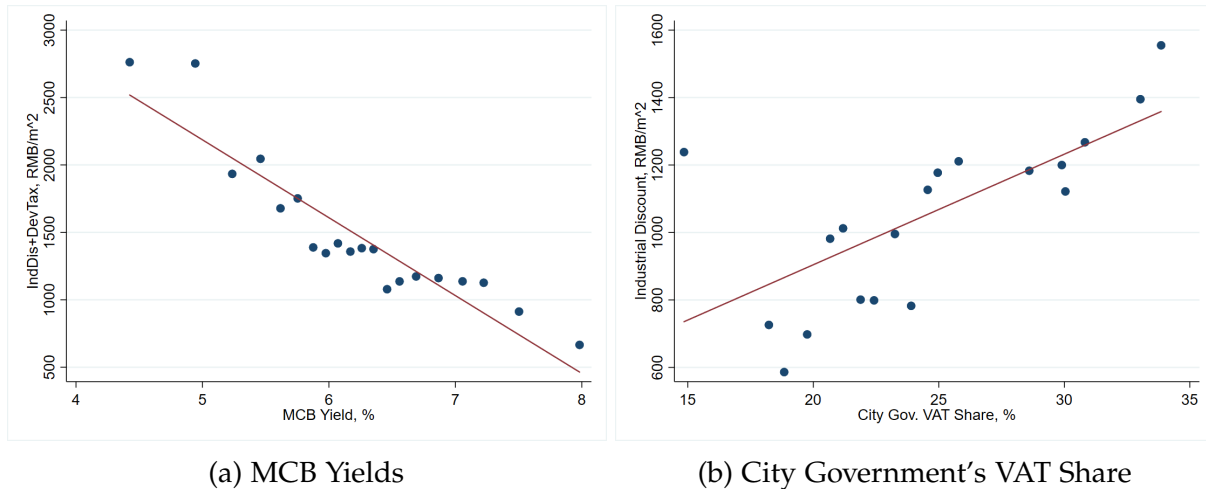


Figure 5: Industrial Discount, MCB Yield and City Government Tax Share

Note: Panel (a) plots bin scatter of $IndDisc_{c,t}$ 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 $IndDisc_{c,t}$ against the city government's VAT share in year t for the sample period 2007-2019.

5 City Discount Rates and Tax Sharing

We posit that local governments' decision to sell industrial versus residential land reflects a tradeoff between upfront sale revenues and future tax revenues. This has two implications for how changes in central government policy and market conditions changes affect local governments' land sale decisions. First, more patient local governments should sell more industrial land: when local governments' municipal bond yields decrease, so borrowing costs in financial markets are lower, industrial land sales should increase, and industrial discounts should increase. Second, policy changes which cause local governments to capture a larger share of industrial tax revenues generated by industrial land sales should increase the amount of industrial land sold by local governments, and industrial discounts should increase.

We show suggestive evidence for both hypotheses in the cross-section of city-years in Figure 5. The left panel shows that municipal corporate bond yields are significantly negatively correlated with industrial discounts, and the right panel shows that the fraction of VAT taxes captured by city governments is significantly positively correlated with industrial discounts, as we conjectured. In the rest of this section, we analyze these two relationships in detail.

5.1 Government Discount Rates

Panel (a) of Figure 5 provides suggestive evidence that governments with higher cost of capital have lower industrial discounts. We proxy the city government’s cost of capital using the issuance yield of municipal corporate bonds (MCBs) which are bonds issued by local government affiliated enterprises set up for financing purposes. A possible endogeneity concern is that certain forces may affect both MCB yields and industrial discounts, so this relationship cannot directly be interpreted as causal. To address this concern, we build on [Chen et al. \(2020\)](#) and use an instrumental variable for MCB yields related to China’s four-trillion stimulus plan in 2009.

In response to the global financial crisis, the central government initiated a large fiscal stimulus plan which involved additional fiscal spending of roughly four trillion RMB to be conducted in 2009-2010. Local governments responded by increasing investment in infrastructure, which has long-lasting effects on the local government’s fiscal position in the future and hence on future bond yields. Across different provinces, the responsiveness of local officials depends on their tenure clock. [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. Local government officials’ tenure is plausibly related to investment choices in 2009 because the incentive to comply with the central government in general increases with the governor’s term.³¹

Following [Chen et al. \(2020\)](#), we construct an instrument, $LateTerm_c$, 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. In the first stage, $LateTerm_c$ is negatively correlated with the MCB yield in subsequent years, and in particular during 2012-2019. This is consistent with greater infrastructure investment in 2009 leading to a stronger future fiscal position, for example in the form of greater values of land inventory with well-developed infrastructure and ready for sale and being used as collateral. The first stage is strong and statistically significant: the F-statistic for 2012-2019 is 28.1.

The exclusion restriction for the instrument is that these fiscal changes are only correlated with the future industrial discounts through changes in MCB yields. In particular, the exclusion restriction requires that the size of the governments’ land inventory, which is affected by $LateTerm_c$, does not directly affect the choice of what mix of residential

³¹More broadly, this is related to the literature on China’s political economy that links local officials’ promotion to their incentives of pursuing local economic growth during different stages of their terms ([Ru, 2018](#)). Moreover, the city government has a strong incentive to comply with 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](#)).

or industrial land to sell.³² Moreover, to avoid the direct effect of governor term in 2009 on land allocation, we will apply the instrument to sample starting from 2012. [Chen et al. \(2020\)](#) show that thanks to the anti-corruption campaign launched in 2012, there is negligible correlation between governor term in 2009 and in future years after 2012.

We then instrument MCB yields by LateTerm_c and estimate the causal effect of MCB yield shifts on industrial discounts, using the following specification:

$$\text{IndDisc}_{c,t} = \beta \times \text{MCBYield}_{c,t} + \sum_{\tau} \gamma'_{\tau} \cdot \mathbf{1}_{t=\tau} \cdot [X_{c,2008}^1, X_{c,t}^2] + \epsilon_{c,t}, \quad (20)$$

where $\text{MCBYield}_{c,t}$ is the average yield of MCB bonds issued by city c year t and weighted by issuance amounts.³³ To separate our estimation sample from the potential direct effect of the governor's term in 2009, we estimate Eq. (20) based on the sample period 2012-2019. We control for time-varying effects of two sets of city-level economic conditions: the first is ex-ante measures, $X_{c,2008}^1$, 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 second is ex-post measures, $X_{c,t}^2$, which includes the growth of GDP, land price and industrial output from 2008 to year t . The ex-post conditions are included to control potential channels through which LateTerm_c might affect the outcome variable and hence invalidate the exclusion restrictions.

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

In Panel B, we proceed to test whether municipal bond yields also affect the *quantities* of residential and industrial land sold, by substituting the dependent variable in Equation (20) with the difference between industrial and residential land supply per capita. In line with our hypothesis, when MCB yields are higher, residential land sold per capita

³²[Chen et al. \(2020\)](#) show that provinces with greater stimulus bank loans in 2009, due to future refinancing needs, experience faster MCB growth and more shadow banking activities during 2012-2015. [Chen et al. \(2020\)](#) are concerned with a pure quantity implication, while the price implication of 2009 stimulus bank loans on future MCB yields is ambiguous, exactly because of the expanded land inventory mentioned here.

³³The 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.

³⁴In appendix D.2.2, with the same specification as Eq. (20), we also find a significant and negative causal effect of the MCB yields on the city's upfront developer taxes.

Table 5: Industrial Discount and Municipal Corporate Bond Yield

Panel A: Effect on Industrial Land Discount

Specification	OLS	OLS	OLS	IV	IV	IV
Dep Var: IndDisc	(1)	(2)	(3)	(4)	(5)	(6)
MCBYield, %	-577.5*** (-9.105)	-345.4*** (-6.134)	-259.8*** (-5.349)	-1,823*** (-7.472)	-2,534*** (-3.013)	-2,558** (-2.511)
Ex-ante Controls	No	Yes	Yes	No	Yes	Yes
Ex-post Controls	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,547	1,543	1,541	1,547	1,543	1,541
R-squared	0.326	0.448	0.550	-0.783	-1.978	-1.890
#City	277	276	276	277	276	276
F statistic				32.68	8.024	6.945

Panel B: Effect on Industrial versus Residential Land Supply

Dep Var:	(Ind-Res)/Pop	Ind/Pop	Res/Pop
	(1)	(2)	(3)
MCBYield, %	-0.504** (-2.287)	-0.234 (-0.986)	0.253** (2.193)
Ex-ante Controls	Yes	Yes	Yes
Ex-post Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,629	1,629	1,629
R-squared	-0.027	0.070	-0.292
#City	298	298	298
F statistic	30.30	30.30	30.30

Note: This table shows the effect of City MCB yields, i.e., the average yields of MCBs weighted by the bond size. Panel A reports the effect on industrial land discount: Columns (1)-(3) report the OLS estimation results and Column (4)-(6) report the 2SLS estimation results where the City MCB yield is instrumented by $LateTerm_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. Panel B reports the 2SLS estimation results for the industrial land supply relative to residential, all in sq.me. per 100 people. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

increases, industrial land sold per capita decreases (though insignificantly), and the difference between industrial and residential land sold per capita decreases. In terms of magnitude, when MCB yield increases by 1%, annual industrial land supply will exceed residential land supply by 0.5 square meter per 10 thousand people.

The finding that governments' bond yields are associated with land zoning decisions and industrial discounts implies that city governments' land allocation decisions can be entangled with their liquidity management. The "land finance" system – the fact that land sales are a large source of local governments' revenues – implies that, if city governments need funds urgently and cannot borrow at low rates in bond markets, they may sell more residential land and less industrial land, even if there is not increased demand for residential land. While we analyze the cross-section in our regressions, our results also have implications for the time series: if the Chinese municipal bond market were to become distressed, one possible knock-on effect would be a decrease in the amount of industrial land sold relative to residential land.

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. As we describe above, while city governments keep almost the entirety of their land sales revenue, the value-added, corporate income and business taxes are all shared between the city and upper-level governments. In this subsection, we investigate the relationship between industrial 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.³⁵ Although the actual share of VAT that accrues to the city governments may underestimate the extent to which the city governments internalize tax revenues from industrial land sales, 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

³⁵ Wu and Zhou (2015) show that the city government VAT share tends to be higher if there is less variation in economic development across cities in the province, if the city's industrial sector is more developed, and if there are less state-owned firms controlled by the province governments.

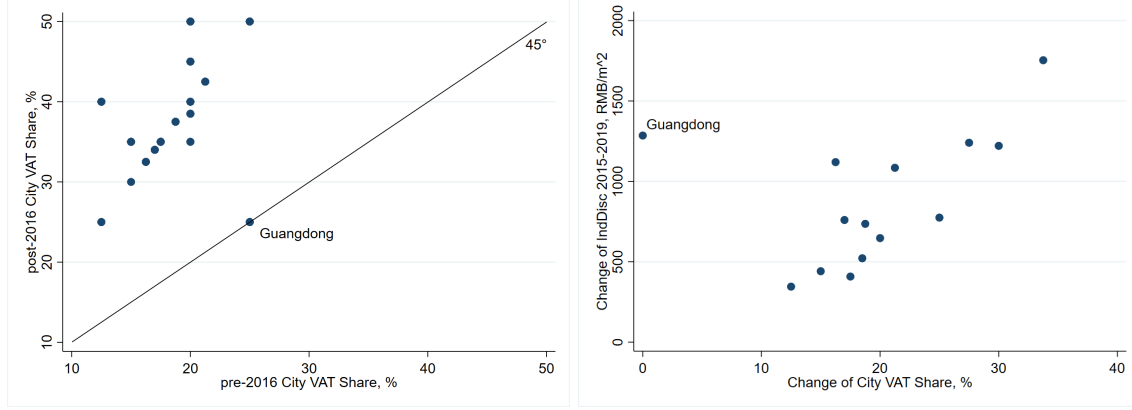
discount, we analyze a change in tax-sharing schemes in 2016. Before May 1, 2016, the central government takes 75% of the value-added taxes and the remaining 25% goes to the provincial and city governments. On May 1, 2016, the central government launched a major tax code change—the so-called "Business 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 value-add taxes retained by the local governments increased from 25% to 50%.³⁶ 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 allocation deci-

³⁶Local 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.

sions respond to these changes in city VAT shares:

$$y_{c,t} = \alpha_c + \gamma_t + \sum_{\tau \neq 2015} \beta_\tau \times \mathbf{1}_{t=\tau} \times \Delta \text{VATShare}_c + \varepsilon_{c,t}, \quad (21)$$

for city c in year t , with city and year fixed effects. In Eq. (21), 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}). The estimation results reported in Table 6 support this hypothesis. We observe a significant and positive treatment effect on the industrial land discount in all 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.

In Columns (2) and (3), we investigate the industrial and residential land price separately. Consistent with our framework, we find that an increase in the share of industrial tax revenues that accrue to the local government tends to increase residential land prices, and decrease industrial land prices. The effect on residential land prices is

quantitatively larger, likely because the levels of residential land prices are much higher.³⁷

Table 6: City VAT Share and Industrial Land Discount

Dep Var:	Price			Quantity		
	IndDisc	$(1 - \lambda)p^{res}$	p^{ind}	(Ind-Res)/Pop	Res/Pop	Ind/Pop
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta VATShare \times$						
Year=						
2012	-0.156 (-0.0136)	-1.965 (-0.188)	-1.810 (-1.032)	1.623 (1.490)	-0.284 (-0.568)	1.506 (1.270)
2013	-7.514 (-0.927)	-7.961 (-0.987)	-0.447 (-0.461)	0.961 (0.931)	0.719 (1.284)	1.627 (1.535)
2014	-1.192 (-0.0790)	-0.603 (-0.0390)	0.589 (0.605)	-0.291 (-0.381)	0.284 (0.766)	-0.0958 (-0.127)
2016	21.90*** (3.173)	20.66*** (2.989)	-1.245** (-1.978)	0.0433 (0.0627)	-0.641* (-1.721)	-0.748 (-1.008)
2017	43.42*** (3.941)	41.42*** (3.705)	-2.001*** (-2.605)	1.470* (1.762)	0.762 (1.483)	2.152** (2.210)
2018	26.25** (2.276)	25.10** (2.156)	-1.148 (-0.855)	4.000*** (3.679)	0.174 (0.308)	4.104*** (3.392)
2019	34.17*** (3.134)	33.84*** (3.059)	-0.325 (-0.266)	0.967 (0.976)	0.164 (0.322)	1.011 (0.968)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,062	2,062	2,062	2,217	2,217	2,217
R-squared	0.831	0.846	0.836	0.705	0.760	0.661
#City	258	258	258	280	280	280

Note: This table shows how the change in city VAT share affects industrial land discounts and the industrial land supply relative to residential. The sample includes all the municipal cities but those in Guangdong for which we have the industrial discount estimates from 2012-2019 for Column (1)-(3), and all the municipalities but those in Guangdong for Column (4)-(6). The treatment variable, $\Delta VATShare$, is in percentage and the land supply is sq.me per 100 people. Standard errors are clustered by cities. Robust t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Columns (4)-(6) of Table 6, we examine the impact of intergovernmental tax sharing on the quantities of industrial and residential land sold, by substituting the dependent variable in Equation (21) with the difference between industrial and residential land supply per capita.

³⁷Although 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.

In Column (4), consistent with the first hypothesis, an increase of the tax share of the city government results in a shift in land supply towards industrial relative to residential uses. In Column (5)-(6), we observe that local governments experiencing a higher increase in their VAT share immediately cut residential land supply, and increase industrial supply over the two years following the policy change.

Our evidence on price is stronger than that on quantity. There are two possible mechanisms through which the industrial discount adjusts. First, the city government may change land allocation in the future, with an immediate adjustment in prices (and 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 transaction price, buyers who know that more future taxes go to the local government may ask for a greater industrial discount. The second mechanism implies no changes on relative land supply. The short-run rigidity of land supply and the price adjustment through negotiation may explain the weaker effect on quantity.

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.

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

	Obs	Mean	Std Dev	Obs	Mean	Std Dev
<i>A. Industrial Lands Characteristics</i>			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
<i>B. Firm Characteristics</i>			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.

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.4](#).

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.

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.

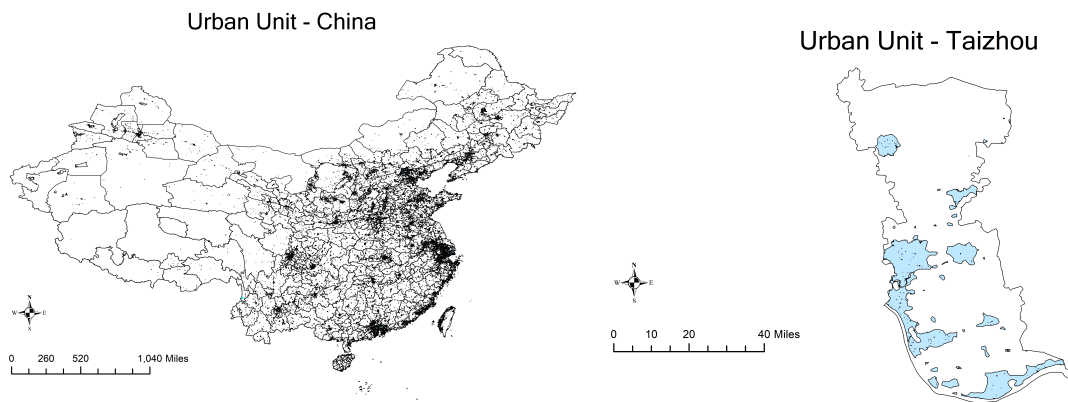


Figure A.1: Examples of Urban Units.

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.

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.

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:

$$0 = \frac{1}{r^{gov}} k\tau f'(L_I) + P_I - \sigma_I^{-1} - (1 + \tau^R) P_R + \sigma_R^{-1} \quad (22)$$

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 (22) implies that in equilibrium, the marginal effect of land on tax revenues is:

$$\frac{k}{r^{gov}} \tau f'(L_I) = (1 + \tau^R) P_R - P_I - (\sigma_R^{-1} - \sigma_I^{-1}) \quad (23)$$

The IRR can then be written as

$$IRR^{ind} \equiv \frac{\tau f'(L_I)}{(1 + \tau^R) P_R - P_I} = \frac{r^{gov}}{k} \left(1 - \frac{\sigma_R^{-1} - \sigma_I^{-1}}{(1 + \tau^R) P_R - P_I} \right) \quad (24)$$

Equation (24) 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

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

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 (23) as:

$$\frac{k}{r^{\text{gov}}} \tau f'(L_I) = (1 + \tau^R) P_R - P_I - \left(\frac{(1 + \tau^R) P_R}{\epsilon_R} - \frac{P_I}{\epsilon_I} \right) \quad (25)$$

Taking derivatives with respect to k on both sides of Equation (25), we get:

$$\frac{d((1 + \tau^R) P_R - P_I)}{dk} = \frac{\tau f'(L_I)}{r^{\text{gov}}} + \frac{k}{r^{\text{gov}}} \tau f''(L_I) \frac{dL_I}{dk} + \frac{d(1 + \tau^R) P_R}{dk} \frac{1}{\epsilon_R} - \frac{dP_I}{dk} \frac{1}{\epsilon_I} \quad (26)$$

Equation (26) 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 (26) simplifies to

$$\frac{d((1 + \tau^R) P_R - P_I)}{dk} = \frac{1}{r^{\text{gov}}} \tau f'(L_I) + \frac{d(1 + \tau^R) P_R}{dk} \frac{1}{\epsilon_R} \quad (27)$$

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 (27) are positive. The increase of k will increase the upfront industrial discount plus the developer tax revenues.

Effect of Imperfect Demand Elasticities in Land Markets. When land sales have price impact, the marginal revenue from incremental land sales differs from the price of

land, which we use to compute IRRs. Formally,

$$\text{IRR}^{\text{ind}} = \frac{r^{\text{gov}}}{k} \times \left[1 - \frac{\overbrace{\sigma_{\text{res}}^{-1} - \sigma_{\text{ind}}^{-1}}^{\text{wedge in inverse semi-elasticities}}}{\text{IndDisc} + \text{DevTax}} \right], \quad (28)$$

where σ_{res} (σ_{ind}) is the negative demand semi-elasticity of residential (industrial) land.³⁸ 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 (Harvey and Jowsey, 2019).³⁹ We therefore would expect the term in brackets in Eq. (28) to be less than 1. Thus, once price impact is considered, IRR^{ind} will tend to be low. Industrial land looks like an unattractive investment which the government overinvests in, but this is because governments are unwilling to sell more residential land because of the greater price impact that has. In other words, with price impact, the industrial discount overestimates the marginal revenue from selling parcels as residential instead of industrial land, since marginal land sales depress prices of inframarginal land parcels.

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”.⁴⁰ Since we only have data on those numbers between 2010–2014 and we need to use lagged budget revenue to adjust

³⁸In 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.

³⁹One reason for household immobility is China’s “hukou” residence restrictions (Li et al., 2017).

⁴⁰Note 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.

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.⁴¹

For the auxiliary cost associated with providing public services to new residences,⁴² 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 Land Characteristics: Industrial versus Residential

Figure A.2 shows that the distribution of land characteristics (i.e., land area and distance to urban center) for industrial land has similar support to that for residential land. Figure A.3 shows the distribution of the R-squared of the pricing functions (5) and (7) across different samples based on city-period combinations.

C.3 Marginal Land Zoning and Industrial Discounts

In the main text, we estimate the industrial land discount for the *average* land parcel. One concern is that, when considering selling slightly more residential versus industrial land, the government in fact considers adjusting land use for a particular set of marginal

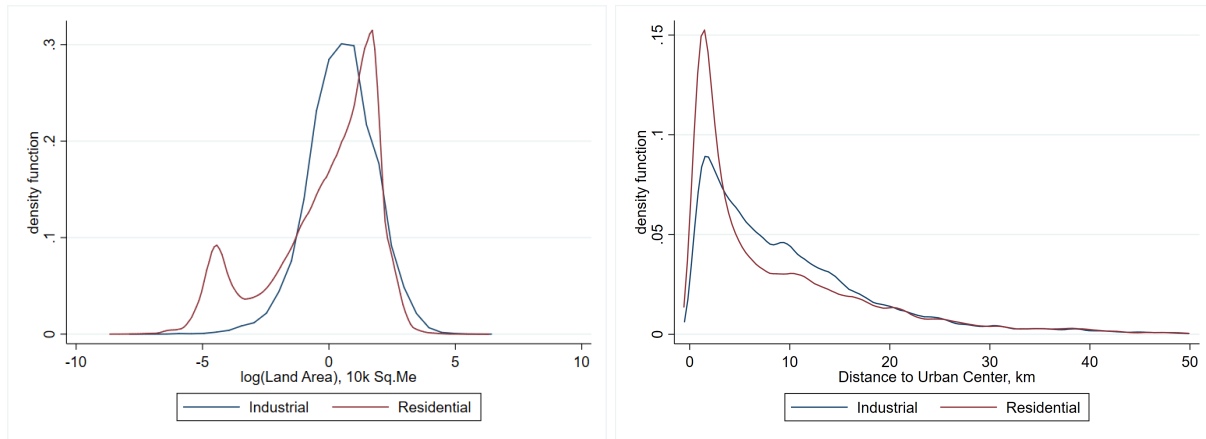
⁴¹There is also no data on the time lag between land reserving and land sales, so we chose to take the averages of lagging one to three years. Specifically, we take the total budget compensation between 2010 and 2012, divide it by the total budget revenue between 2011-2013, 2012-2014, and 2013-2015, 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 .

⁴²See the [2012 Code for Planning Standards](#), Item 4.3.2.

Table A.2: Lambda Estimates

Price Tier	Sample Period	
	2007-2010	2011-2019
High	0.073*** (4.231)	0.171*** (7.404)
Medium	0.079*** (6.666)	0.146*** (7.231)
Low	0.094*** (6.386)	0.077** (2.798)
Total	0.087*** (10.737)	0.114*** (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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.



(a) Land Area (b) Distance to Urban Center
Figure A.2: Land Characteristics: Industrial versus Residential

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

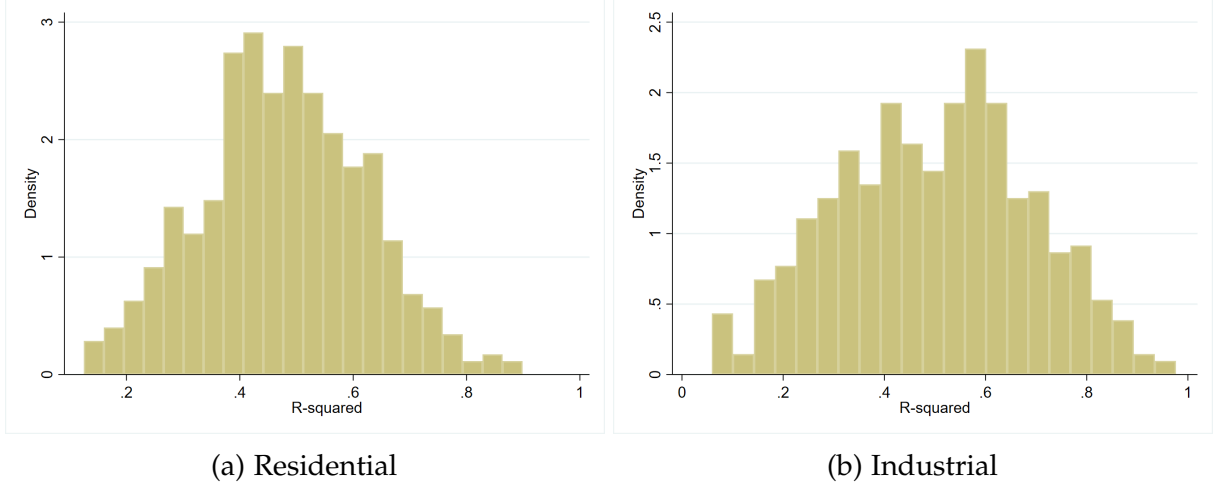


Figure A.3: Performance of the Land Pricing Model

Note: These two graphs show the distribution of R-squared of the two pricing functions, (5) and (7), across different samples defined by city-period combinations.

land parcels, and it is the industrial discount for these marginal land parcels that we should compare with the marginal future tax revenues. For example, if industrial and residential land parcels are strictly segregated by a line, then when the government adjusts land allocation, only land parcels close to the line are affected. In this appendix, we demonstrate an approach to identify marginal land parcels; this allows us to calculate the city-level industrial discount estimates in a way that puts more weight on the marginal land parcels.

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

$$U_{i,t}^{res} = g(X_i) + \xi + \epsilon_{i,t}^{res} \quad (29)$$

In Equation (29), $g(x_i)$ captures land i 's tendency to be used as residential, and ξ represents the government's overall tendency to sell residential land versus industrial land. We adopt a Logit model for the land use decision. The probability of a parcel with characteristics X_i being sold as residential is:

$$p(X_i, \xi) \equiv \frac{\exp(g(X_i) + \xi)}{1 + \exp(g(X_i) + \xi)} \quad (30)$$

Let $f(X)$ be the multidimensional density function over land parcel characteristics, such as location, land size, and other characteristics. Given ξ , the expected total industrial land discount due to supply of industrial land and the total industrial land supply are:

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

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

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

Now, by differentiating (30) and rearranging, we can find that:

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

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

$$\text{Area}(X) \cdot p(X, \xi) (1 - p(X, \xi)) \quad (31)$$

Expression (31) states that the marginal industrial land discount loads more on land parcels with higher $p(X, \xi) (1 - p(X, \xi))$. Intuitively, this term is $\frac{\partial p(X, \xi)}{\partial \xi}$, which captures how much small changes in the government's preference to sell residential land changes the *likelihood* of a given parcel i being sold as residential. The adjustment term is maximized when $p(X, \xi) = 0.5$, and is smaller when the probability of residential sales is very large or very small.

This framework captures the intuitive idea that parcels which have an intermediate likelihood of being sold as residential land are most "marginal". If the government is close to indifferent between selling parcel i as residential or industrial, this parcel is very marginal: small changes in the government's preference for industrial land will cause the parcel to be much more likely to be sold as residential or industrial. In contrast, when $p(X, \xi)$ is very close to 1 or 0, the government has a strong preference to sell the parcel as

Table A.3: Estimating Industrial Discount With Marginal Land Zoning

Panel A: Model Predicted Residential Land Zoning

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

Panel B: National Average Industrial Land Discount

Model	IndDisc
Simple Average	1012.83
Logit	1029.34
Nearest neighbor	1037.93

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

industrial or residential; small changes in ξ will not change the likelihood of selling the parcel as industrial versus residential substantially.

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

$$\hat{p}_i = \frac{\exp(X_i\hat{\beta})}{1 + \exp(X_i\hat{\beta} + \xi)}$$

The second approach is the nearest neighbor. This approach makes use of the fact that land parcels with the same use tend to cluster together. For each land parcel i in

the urban unit u , we select all the land parcels within a distance of k_u and calculate the share of these neighbors being residential, $p_i(k_u)$, as an estimate of the probability of residential zoning for i . Then for all the land parcels in the urban unit u during 2007-2019, we choose k_u to maximize the log likelihood of the observed outcome:

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

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

The results are shown in Table A.3. Panel A shows the performance of the two models in predicting land uses. Both models do reasonably in predicting the land use, while the nearest neighbor model performs slightly better than the Logit model. Panel B shows national average industrial discounts in the baseline specification, as well as using the re-weightings from the Logit model and the nearest neighbor model. We find that the estimates of industrial discounts barely change with the re-weightings.

C.4 Panel Imbalance

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

Figure A.4 shows the results of this test in the form of kernel densities of past-year sales, separately for firms that do and do not attrite in a given year. We see the two distributions are strikingly similar. If anything, firms near the 2011 censoring boundary (denoted by the second of the two vertical dashed lines in the figure) are disproportionately likely to be *not* censored. We are reassured that the role of censoring is likely modest in generating panel imbalance.

We also examine whether panel imbalance varies by treatment status (land purchase). Table A.4 shows the survival rates of the treated and matched control firms for each event year, i.e., the percentage of firms remaining in the sample. By construction, all the firms

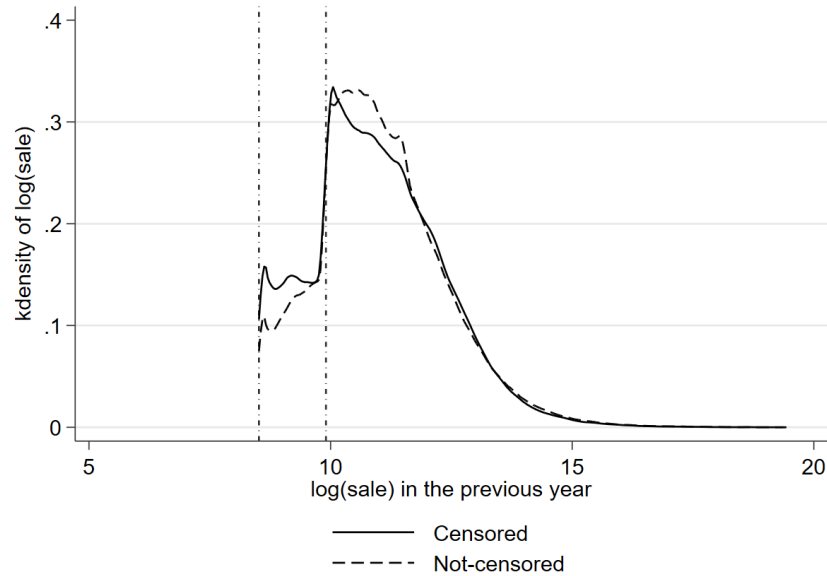


Figure A.4: Distribution of Log(Sale) in the Previous Year

Note: This figure reports the kernel densities of the past year $\log(\text{sale})$ 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.

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

Table A.4: Survival Rates of the Matched Sample

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

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

C.5 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 share of GDP. Hulten's theorem is significant in the sense that sales summarize the macroeconomic impact of microeconomic shocks and we do not 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 [Baqae 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 [Baqae 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):

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

where $x_{i,j}$ are intermediate inputs of good j used in by 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

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

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:

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

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.

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

C.6 Estimating Marginal Industrial Tax Rates

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

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

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

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

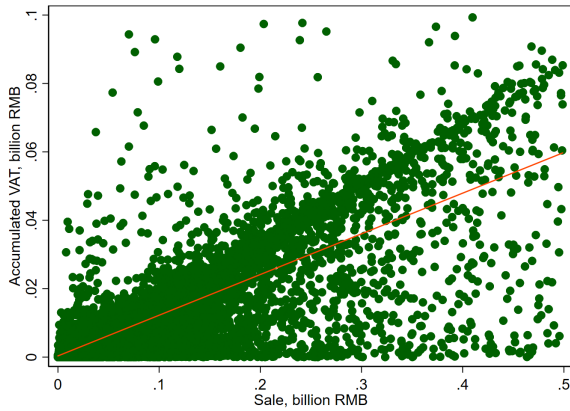
$$ITF_{j,t} = (S_{j,t} - COGS_{j,t}) \cdot \psi_t$$

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

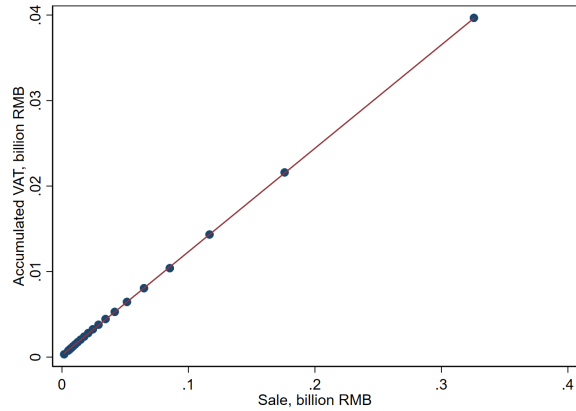
In the end, our estimate of the firm tax rate is $(12.10\% + 5.77\%) = 17.87\%$

C.7 Complementary Evidence of Land Tax Yields

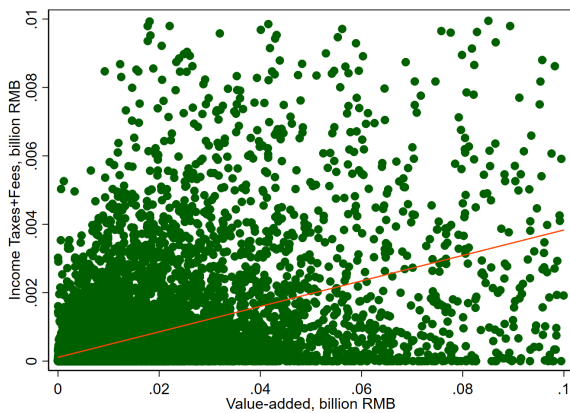
Figure A.6 plots the average VAT per square meter of industrial land by province (Panel (a)) and the minimum tax requirement by industry (Panel (b)).



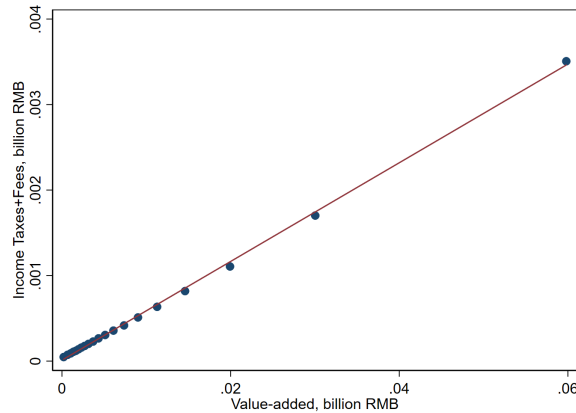
(a) Scatter Plot: Accu. VAT vs Sale



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



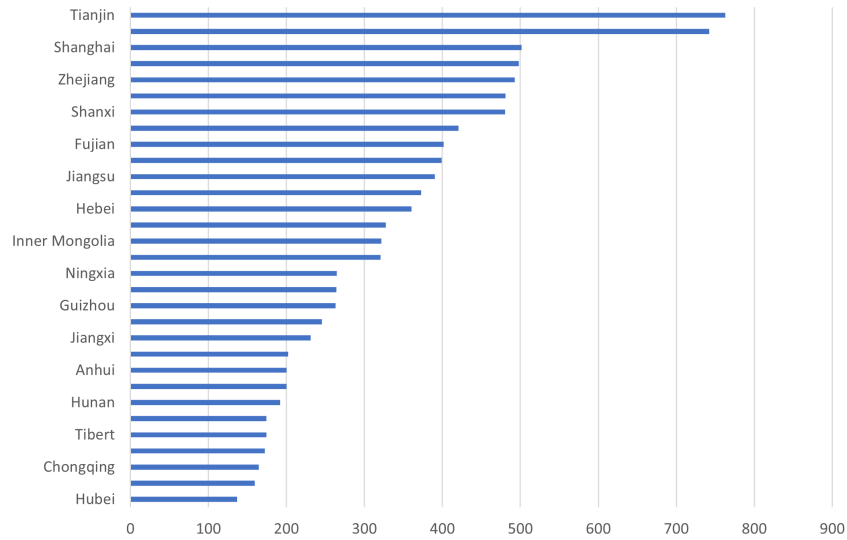
(c) Scatter Plot: Income Tax + Fees vs VA.



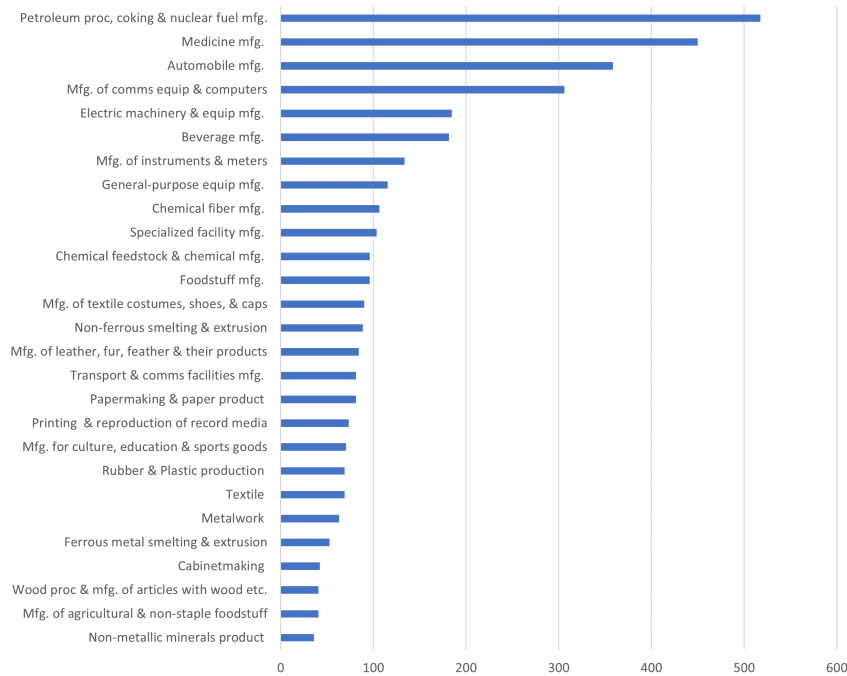
(d) Bin Scatter Plot: Income Tax + Fees vs VA.

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

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



(a) Total VAT Over Industrial Land for Each Province, 2011, RMB/m²



(b) Requirement on Minimum Tax Payment by Firms on Industrial Land, RMB/m²

Figure A.6: 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/m².

C.8 Estimating Marginal Residential Tax Rates

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

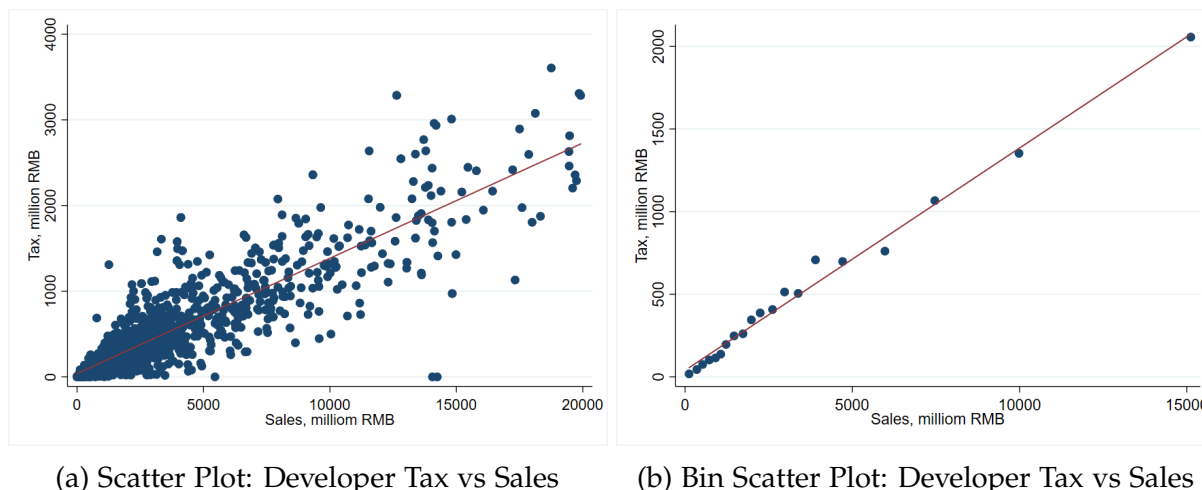


Figure A.7: Marginal Total Tax Rate of Home Developers

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

C.9 Classification of Targeted Industries

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

C.10 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.6, we estimate that for one RMB increase in firm sales, the value-added taxes increase by 12.10%, corporate income taxes increase by 3.33%, and other taxes and fees increase by 2.44%. The value-added and corporate income taxes are shared with upper levels of governments, and the other taxes and fees all accrue to the city governments. Therefore, the city government share of industrial taxes is:

$$\text{IndTaxShare}_c = \frac{12.10\% \times \text{VATShare}_c + 3.33\% \times \text{ITShare}_c + 2.44\%}{12.10\% + 3.33\% + 2.44\%} \quad (34)$$

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

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

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

To aggregate IndTaxShare_c to the national level in a way comparable to the estimation of IRR during 2007-2010, we calculate the average 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 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 land sales. When we include cities in Guangdong when estimating Equation (21), 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.6: as predicted, cities allocating more industrial land were substantially more likely to be rewarded.

The majority of these policies were applied only in the Guangdong province.⁴³ 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.6: Industrial Land Supply and Reward in Guangdong

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

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

⁴³Two 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 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.

D.2.1 City's Developer Tax Rate

In this section we describe how we calculate the developer's tax rate $DevTaxRate_{c,t}$, 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:

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

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:

$$CityDevTaxRate_{c,t} = E_t\left[\frac{d IT_{i,t}}{d Sales_{i,t}}\right] \times ITShare_{c,t} + E_t\left[\frac{d TS_{i,t}}{d Sales_{i,t}}\right] + E_t\left[\frac{d (Sales_{i,t} - COGS_{i,t}) \times VATRate_t}{d Sales_{i,t}}\right] \times VATShare_{c,t}$$

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

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

Table A.7: Developer Taxes and Municipal Corporate Bond Yield

Specification	OLS	OLS	IV	IV
Dep Var: DevTax	(1)	(2)	(3)	(4)
CMCBYield, %	-395.1*** (-6.778)	-257.0*** (-6.216)	-1,183*** (-6.093)	-1,490*** (-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 $LateTerm_c$, i.e., an indicator of whether the provincial governor had been in office for at least three years in the beginning of 2009. The sample period is from 2012-2019. Standard errors are clustered by cities. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the city governments, as follows:

$$CityDevTax_{c,t} = P_{c,t}^h \times FloorRatio_c \times CityDevTaxRate_{c,t}$$

D.2.2 Government Discount Rates and Developer Taxes

With the same specification as Eq. (20), we replace the dependent variable with the city's developer taxes $CityDevTax_{c,t}$. The result is shown in Table A.7. 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. (21), we then use developer taxes as the dependent variable. As shown in Table A.8, 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.8: City VAT Share and Developer Taxes

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

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