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Industrial Land Policy and Economic Complexity of Chinese Cities

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Industrial Land Policy and Economic Complexity of Chinese Cities

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Abstract: Economies producing more complex products tend to be wealthier and grow more quickly. Therefore, a key issue for cities around the world is to develop new specializations into more complex industries. In China, local governments tend to use industrial land subsidy as a policy tool to attract new firms in desired industries and promote industrial growth. However, relatively little is known about the impact of this policy tool on the economic complexity of Chinese cities. Drawing upon the recent literature on the principle of relatedness and economic complexity, this paper investigates the impact of this industrial land policy (ILP) on the diversification of Chinese cities into more complex industries. The empirical results support our hypothesis that those cities providing higher intensity of land subsidy are more likely to enter new industries, in particular the most complex ones.

Keyword: Economic Complexity; Industry Complexity; Industrial Land Policy; Industrial Diversification

1 Introduction

Over the last decades, industrial policies have been increasingly implemented by countries to enhance productivity, upgrade industrial structure, and foster economic growth. While these policies are usually disputed by scholars as they may reduce competition and enable governments to pick up winners, recent studies have argued that industrial policy is vital to industrial development and diversification (Aghion et al., 2015; Rodrik, 2004, Balland et al., 2019). Good policy interventions can decrease concentration of industry, induce innovation, foster knowledge transfer, and reallocate resources across sectors, which would in turn support regional branching and product development (Lee and Lim, 2001; Neffke et al., 2011; Uhlbach et al., 2017); while poorly-designed policies might lead to resource misallocation, productivity and welfare losses. Policy interventions have the potential to jump-start economic development, but for this potential to realize and scale it is important to find the regional ecosystem that matches with the often nationally designed industrial plan. This is why industrial and innovation policy, such as the Smart Specialization Strategy in Europe, are increasingly place-based and build on the idea that cities and regions should invest in industries that matches their economic structure (Balland et al., 2019). As economies producing more complex products tend to be wealthier and grow more quickly a key policy challenge is to facilitate new specializations into the most complex industries.

In China, the extensive use of industrial policies has been one of the most prominent features characterizing its unprecedented economic growth since the 1980s. For the sake of career promotions, Chinese local officials have strong incentives to actively intervene in industrial development with various forms of industrial policies such as industrial parks (special economic zone) and land-related policies (Li and Zhou, 2005, Chen, Li and Zhou, 2005; Zheng et al., 2014). The effect of such industrial policies on urban economic growth has been widely investigated. For instance, many studies find that industrial parks can exert strong and positive externalities on local economic development (Alder et al., 2016; Lu et al., 2018; Wang, 2013). In addition to industrial parks, land policy is another powerful intervention instrument which has been widely adopted by Chinese local officials to attract investment from both home and abroad, usually in the form of control land allocation, bidding for prosperous investors by offering them with cheap industrial land (Henderson et al., 2019; Huang and Du, 2017; He et al., 2014; Wu et al., 2014). Many studies have argued that land has been a key factor stimulating China's economic growth (Cao, Feng and Tao, 2008; Deng et al., 2010; He et al., 2014; Tao, Liu and Cao, 2010; Wu et al., 2014). However, these studies mainly focus on aggregate economic performance, with relatively less attention paid to investigating the industry-specific effect of industrial land policy at the city level.

The industrial diversification literature has argued that regional development is constrained by existing knowledge and capabilities among industries (Hidalgo et al., 2007). Such a path-dependent process constrains regions' diversification in related domains and prevents less developed regions from branching into new industry space (Hidalgo et al., 2007; Boschma and Frenken 2011; Neffke et al., 2011; Guo and He, 2017). However, some scholars have explored whether extra-regional linkages and policies can affect regional industrial diversification. For instance, Uhlbach et al. (2017) find that EU Framework Programs (FP) have a positive impact on the probability of new specializations of regions and compensate for a lack of local related capabilities. Guo and He (2017) argue that China's "Western Development Strategy" and a number of favorable policies play a significant role in attracting competitive industries and creating new evolution path of industrial development. However, they mainly focus on industrial relatedness and estimate how policy can help regions to enter less related activities, relatively less attention has been paid to investigate whether industrial policy can help regions branch into more complex industries.

With the above research gaps borne in mind, we explore the following research question in this paper: can local governments' industrial land policy (ILP) facilitate the entry of cities in more complex industries?? In doing so, we aim to contribute to the existing literature from three perspectives. First, we move beyond the traditional focus on economic growth in the land use policy literature by investigating how ILP could affect the development of specific industries. Second, we add to the industrial diversification literature by exploring whether the regional industrial branching process (i.e., the capabilities of regions to jump into a new industry space) can be influenced by policy interventions (Uhlbach et al., 2017). Third, by drawing upon the recent literature on complexity (Hidalgo and Hausmann, 2009; Balland and Rigby, 2017; Balland et al., 2019), we further explore whether the possibility of jumping to more complex industry space can be facilitated by ILP.

Using China's annual firm-level survey data, which covers 191 industries in 286 cities at the prefecture level or above[1] during the 2003-2008 period, we find that, on average, cities tend to enter new industries with similar levels of complexity of their existing industrial structure. Cities with stronger industrial land policy (with deep subsidy, i.e., offering relatively higher land subsidy intensity) are more likely to enter new industries and especially those more complex industries. Therefore, industrial land policy might be able to help regions jump into more complex industry space, which further enhances the potential for industrial upgrading and economic growth. These findings are of significance not only for city leaders who need to design more effective industrial policies and make the informed trade-off between the cost and benefit of such policies, but also for firms in their city choice decision.

The remainder of this paper is organized as follows. Section 2 discusses the recent literature on industrial diversification, economic complexity, and China's industrial land policy. Section 3 describes the data and methodology. Section 4 analyzes the empirical results. Section 5 concludes with policy implications.

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[1] They include 282 prefecture-level cities and 4 municipalities directly under the administration of the central government (Beijing, Shanghai, Tianjin, Chongqing). Prefecture-level cities rank below a province/municipality but above a county in China's administrative structure.

2 Literature review

2.1 Institutional background of China's industrial land policy

Since GDP performance is an important factor evaluating the performance of local political leaders and influencing their probability of getting promoted, city leaders will compete with each other and have strong incentives to use various forms of industrial and economic interventions to attract investment, facilitate industrial development and guarantee the economic growth (Li and Zhou, 2005, Chen, Li and Zhou, 2005; Aghion et al, 2015; Wang et al.,2018).

Industrial land policy is one of the most widely used policies by Chinese local officials (He et al. 2014; Huang and Du, 2017; Wu et al., 2014; Zheng and Shi, 2018). In contrast to western countries, urban land in China is state-owned. Local governments have the right to acquire land from rural owners, and then lease it out to other users through either a non-market negotiation or a market auction. Compared to allocating land to residential use which just generates one-time land-leasing revenue (there is no residential property tax in China), allocating land to industrial use (manufacturing enterprises) not only generates future tax revenue but also shapes industrial structure, which are more crucial for a city's economic growth in the long run. At the same time, capital is quite footloose and city leaders are always in fierce competition with each other for productive firms in the advanced industries with higher industry complexity. Therefore, local governments tend to shape the land allocation process and use deep industrial land subsidy (through the non-market one-on-one negotiation way) to compete for the productive firms in their desired industries. (Huang and Du, 2017; Zheng and Shi, 2018).

A growing literature has identified that land is a key factor in stimulating China's economic growth. However, the majority of previous empirical studies about the efficiency of land policy mainly focus on the overall GDP growth or a macro-level measure of industrial upgrade. Most of those studies treat industries as homogenous and ignore the heterogeneity embedded in industries. For example, He et al. (2014) argues land plays an important role in attracting foreign investments and sustaining infrastructure investments, which further indirectly stimulates economic growth. Wu et al. (2014) apply a dynamic game theory approach to evaluate how the low industrial land price affects industrialization. They conclude that such an industrial land premium is crucial to China's urban expansion and leads to China's position as the "World factory". However, this policy results in excessive development of industrial land within the total urban land use structure. Zheng and Shi (2018) argue that industrial land policy has a significant effect on firms' location choice and this impact varies across firm heterogeneity, such as ownership and industry-specific attributes.

2.2 Complexity and industrial diversification

Recent studies have highlighted the significance of complexity in understanding the process of industrial and economic development (Hidalgo and Hausmann, 2009; Balland and Rigby; 2017). As a crucial dimension of tacit knowledge, complexity plays an important role in generating competitive advantage for both firms and regions (Asheim and Gertler, 2005; Kogut and Zander, 1992). Regional industrial structures vary not only in their technological composition but also in their values. Economic complexity, a key factor for the values of economic activities, is crucial to improve the exclusivity and value of product (Simon, 1991). These complex, exclusive, and non-ubiquitous commodities require various capabilities and cannot be easily imitated by others, which however could improve the competitiveness of a region and is beneficial to economic performance in the long run. Since the capabilities embodied in complex industries are scarce and difficult to be replicated, complex industries are beyond the scope of most cities because these cities lack the required capabilities and knowledge that are needed to develop these industries (Balland et al., 2018). Therefore, it is harder to enter the industry space that is more complex than a city's current industrial structure. On the other hand, industries with lower complex knowledge are less competitive and are more easily to be eliminated by other more complex industries with more values. Therefore, regions are more likely to enter new industries that have a level of complexity similar to their current industrial structure.

2.3 Industrial land policy and industrial diversification

In Chinese cities, land allocation and the associated subsidy depend on city leaders' strategic considerations. Some scholars have noticed that land resources are usually allocated by local governments in a way that aligns with their specific development strategies such as stimulating certain industries and competing with neighboring cities (Huang and Du, 2017). For instance, Wang and Yang (2016) argue that local governments tend to use land subsidy to attract firms with positive external effects. Aghion et al. (2015) argue that industrial policies in China such as subsidies and tax holidays can be more effective in improving industrial productivity if they are allocated to more competitive sectors. Guo and He (2017) also argue that favorable policies in China's "Western Development Strategy" can attract advanced industries that are not related to the industrial base of China's western regions, helping those regions to generate a path-breaking industrial development process.

Land, a significant factor of production, is indisputably crucial to the development of manufacturing industries and services. By leasing land with a price that is much lower than the market level, firms in fact receive a kind of financial subsidy from governments. These subsidies make up for the lack of available knowledge and capabilities that are needed to branching into new industry space. As a result, land subsidy reduces the involved risk and cost in developing new industries, which further helps city branch into new industry space. More importantly, city governments' strategy of using industrial land subsidy to compete for more complex industries has its benefit and cost. Those industries will help cities gain comparative advantage and obtain additional rents from complex knowledge and technologies (Balland et al., 2019; Broekel, 2017), which leads to higher economic growth potential. The opportunity cost of such a strategy is the foregone land-leasing revenue (the gap between the market and the subsidized land rents), and the reduced residential land supply which might lead to constrained labor supply and higher housing prices (Glaeser et al, 2005).

3 Data and Methodology

From the above analysis, we can see that Chinese city governments use such an industrial land subsidy as a key preferential policy to compete with other cities for more complex industries. They tend to offer the desired industries with higher complexity level higher subsidy so that they are more likely to attract those industries.

Based on this mechanism, our empirical analysis is to test the hypothesis that, cities offering higher land subsidy intensity later gain more complex industries, which is the outcome of this competition process. If this is true, those industries in turn will help cities gain comparative advantage from complex knowledge and technologies (Balland et al., 2019), which leads to higher economic growth potential.

3.1 Industrial relatedness

Data used to measure industrial structure and growth are retrieved from the Annual Survey of Industrial Firms which was conducted by the National Bureau of Statistics (NBS) in China during the 1998-2008 period. The survey covers all state-owned enterprises and non-state-owned enterprises with sales revenues above 5 million RMB from the mining, manufacturing, and public utility industries. [2]The survey collects detailed information on each enterprise including its manufacturing address, employment, gross output, and industrial classification code. According to Brandt et al. (2012), these firms account for roughly 70% of the industrial workforce and 90% of the industrial output in China. We use SIC codes (GB/T4754-2002) to match each firm's industrial type and then aggregate the firm-level output data to the three-digit sector level for each city at the prefecture level or above.

We then calculate revealed comparative advantage (RCA), relatedness and relatedness density (Density) to measure industrial development and industrial structure (Hidalgo et al., 2007). The RCA concept and measurement have been used in many different contexts, such as patents, publications, occupations and industries (Hidalgo et al., 2018). RCA demonstrates whether a city has a relative advantage or disadvantage in a specific category of industries, which enables us to observe whether a city can gain new industries with the help of industrial land policy. The relatedness concept is based on the idea that if two industries are more related, they demand similar inputs, such as capital, infrastructure, knowledge etc., and are more likely to be produced together. Relatedness density is used to measure the distance between an industry and a city's existing industrial structure, allowing us to see whether a city tend to develop more related industries.

[2] In this paper, we look at the manufacturing sector (and also mining and public utilities), which contains 191 3-digit industries.

We first calculate the revealed comparative advantage (RCA) of each three-digit industry in each city. An industry i has revealed comparative advantage (RCA=1) in city c in year t if its location quotient (based on industrial output) is more than one (Hidalgo et al., 2007). [3]The formal specification is as follows:

$$RCA_{i,c,t} = 1 \; if \; \frac{industry_{i,c,t} / \sum_i industry_{i,c,t}}{\sum_c industry_{i,c,t} / \sum_c \sum_i industry_{i,c,t}} > 1 \qquad (1)$$

where $industry_{i,c,t}$ represents the output of industry i in city c in year t. The above equation shows that a city c has RCA in industry i in year t if the proportion of industry i in the city's product portfolio is higher than the average share of the industry to the country's total. A bipartite network that connects a city and the product it produces can be represented as a city-product adjacency matrix $M_{i,c}$, where $M_{i,c} = 1$ if city c has RCA in industry i and 0 otherwise.

We then calculate relatedness between industries i and j, which is defined as the minimum of the conditional probability that the two industries would have RCA in the same locations (Hidalgo et al. 2007). Higher relatedness indicates that the two industries are more likely to co-locate in the same location.

$$\varphi_{i,j,t} = \min\{P(RCA_{i,c,t} > 1 | RCA_{j,c,t} > 1), \; P(RCA_{j,c,t} > 1 | RCA_{i,c,t} > 1)\} \quad (2)$$

Finally, we measure industry relatedness density of a specific industry i in city c in year t as follows. This indicator is essentially the average RCA of all other existing industries in a given city weighted by their relatedness with this specific industry. An industry with a higher level of density in a given city means that this industry is surrounded by many well developed industries, which would contribute to the development of this industry.

$$Density_{i,c,t} = \frac{\sum_j RCA_{j,c,t} \varphi_{i,j,t}}{\sum_j \varphi_{i,j,t}} \qquad (3)$$

3.2 Industry complexity of industries and Economic complexity of cities

We follow the method of reflection[4] to calculate the Economic Complexity Index (ECI) of cities and Industry Complexity Index (ICI) of industries (Hidalgo and Hausmann, 2009).[5] This measure has been widely used to The Economic Complexity Index (ECI) reflects knowledge accumulated and shown in economic activities in cities. The counterpart of ECI is the Industry Complexity Index (ICI) which measures the knowledge intensity of an industry. By construction, complexity is driven by two factors: the diversity of a city (the

[3] For the purpose of robustness check, we also define RCA =1 if its location quotient is larger than 2, and 0 otherwise

[4] This method has been applied in many contexts, such as patents (Balland et al., 2018), employment (Farinha et al., 2019) and so on. To compute the level of complexity of industries, we used the MORt function in the EconGeo R package (Balland, 2017).

[5] The distribution of ECI and KCI can be found in Appendix 2 to 5.

number of industries that a city has RCA) and the ubiquity of an industry (the number of cities that have RCA in a specific industry). For example, if only very few cities are specialized in a certain industry (low ubiquity), it is a first indication that the required capabilities might not be available everywhere. To sort out industries that have a low ubiquity because they are complex from the ones that have low ubiquity because they are not attractive we look in a second stage at the diversity of cities that produce this industry. If a city has RCA in numerous industries, then this city is diversified and tend to be more complex. But to score high in complexity, cities need to be specialized in non-ubiquitous industries. Formally, the diversity of a city ($K_{c,0}$) and the ubiquity of an industry ($K_{i,0}$) can be calculated as follows:

$$\text{Diversity} = K_{c,0} = \sum_c M_{i,c} \tag{4}$$

$$\text{Ubiquity} = K_{i,0} = \sum_c M_{i,c} \tag{5}$$

By combining diversity and ubiquity, the economic complexity of cities and industry complexity of industries can be computed over a number of iterations (n):

$$ECI_c = ECI_{c,n} = \frac{1}{k_{c,0}} \sum_i M_{i,c} ICI_{i,n-1} \tag{6}$$

$$ICI_i = ICI_{i,n} = \frac{1}{k_{i,0}} \sum_i M_{i,c} ECI_{c,n-1} \tag{7}$$

Then, we take the $(ICI_i + 1)$ divided by $(ECI_c + 1)$ to reflect the relative complexity level of industry i to city c's specialization basket.[6] When $RCI_{i,c}$ is larger than 1, that means that industry i is relatively more complex than city c's current industrial base, and vice versa.

$$RCI_{i,c} = (ICI_i + 1)/(ECI_c + 1) \tag{8}$$

Figure 1 shows the distribution of the average ECI of Chinese cities at the prefecture level or above during the 2003-2008 period. Generally, we find a pattern similar to the one found in the US with the level of economic complexity being highly concentrated (Balland and Rigby, 2017). Complexity decreases from east to west. Cities with higher level of ECI mainly concentrate in southeastern coastal areas, while those with lower level of ECI are mainly distributed in northern and southwestern areas.

[6] ICI and ECI are standardized index which range from -1 to 1. Considering the existence of negative value, we use $(ICI_i + 1)/(ECI_c + 1)$ to reflect the relative complexity level.

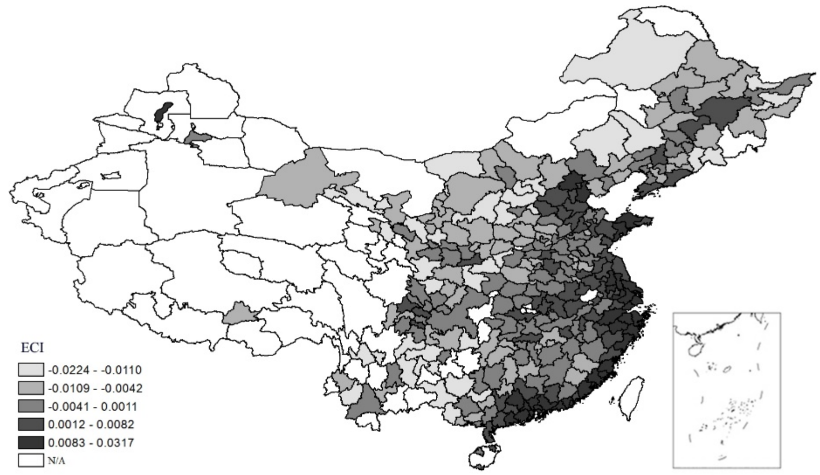


Figure 1. Economic complexity of Chinese cities (2003-2008)

3.3 Industrial land subsidy intensity

Data on industrial land leasing are collected from China Land and Resource Statistic Yearbooks. The dataset includes the leasing area and price of land through negotiation and auction in each city at the prefecture level or above. One-on-one negotiation is the preferred and mainly used way for local governments to lease industrial land, which always yields very low land prices (Huang and Du, 2017); while residential land is always leased through auction, which always leads to high prices. Following the approach of Huang and Du (2017) and Yang et al. (2014), we use negotiation quantity and price as proxies for the quantity and price of industrial land leasing, and those of auction as proxies for the quantity and price of market transactions of non-industrial land.

In this paper we construct three measures for the industrial land subsidy intensity in China: 1) Subsidy intensity; 2) Subsidy price gap; and 3) The land market distortion index developed by Henderson et al (2019) .

First, we construct the subsidy intensity of industrial land leasing as follows:

$$SUBSIDY\ (Subsidy\ intensity) = \frac{(\text{auction}\ price - negotiation\ price) * Leasing\ area}{GDP} \qquad (9)$$

Where $(auction\, price\ - negotiation\, price)$ represents the difference between auction price and negotiation price (both are unit price, per square meter). Here, the auction price can be regarded as the "opportunity cost" of leasing industrial land using negotiation method (what would the extra land price be if it was leased through auction instead of negotiation). We multiply the price difference by the total amount of industrial land leasing area to represent the absolute subsidy (in the sense of opportunity cost) offered by local governments when leasing industrial land. Given that Chinese cities differ significantly in their development levels and economic scale, we divide the absolute subsidy of industrial land leasing by city's gross domestic product (GDP) for the same year to obtain the intensity of each city's industrial land subsidy.

The second measure is $Subsidy\ price\ gap$ which measures land subsidy by the price gap per square meter of land offered by local governments when leasing industrial land, relative to residential land price. This measure is used to estimate the effect of the absolute price subsidy on industrial diversification which could help demonstrate the efficiency of the industrial land policy.

$$SUBSIDY2\ (subsidy\ price\ gap) = auction\ price\ - negotiation\ price \tag{10}$$

The third measure is the land market distortion index developed by Henderson et al (2019). This index is based on city-level hedonic regressions for residential land and industrial land. After running the city-specific and sector-specific hedonic regressions, they predict the hedonic price of a representative land parcel for each city, for industrial use and residential use. They calculate the ratio of residential land price to industrial land price to reflect the extent of local government’s favoritism over industrial land. We use this index to check the robustness of our empirical results.

Figure 2 shows the spatial distribution of average subsidy intensity of industrial land leasing of Chinese cities at the prefecture level or above during the 2003-2008 period. Generally, cities with higher level of land subsidy intensity are provincial capitals, municipalities directly under the central government, or some major cities.

Figure 2. Average industrial land subsidy intensity of Chinese cities (2003-2008)

3.4 Model specification

We use a linear probability model with fixed effects to predict the entry probability of specific industries in Chinese cities at the prefecture level or above. For the purpose of robustness check, we also estimate the model with Probit regression technique, which is presented in Appendix 1. The specification of the entry model is as follows:

$$Entry_{i,c,y} = \alpha_1 * Density_{i,c,y-1} + \alpha_2 * RCI_{i,c,y-1} + \alpha_3 * RCI^2_{i,c,y-1} + \alpha_4 * Subsidy_{c,y-1} + \alpha_5 * Subsidy_{c,y-1} * RCI_{i,c,y-1} + \beta * X_{c,y-1} + \delta_i + \eta_c + \lambda_y + \varepsilon_{i,c,y} \quad (10)$$

where $Entry_{i,c,y}$ is a dummy variable. The value of $Entry_{i,c,t}$ equals one only when city c does not have RCA in industry i for three years before y (year y-3, y-2 and y-1) and gains RCA for three years after y (year y, y+1 and y+2). This three year smoothing is commonly used in the relatedness literature to smooth and avoid RAC fulctuationg anround the threshold. $Density_{\ i,c,y-1}$ is industrial relatedness density, which measures how industry i is technologically related with other existing industries in city c at year $y-1$. $RCI_{i,c,y-1}$ represents the difference in industry complextity of industry i and economic complexity of city c at year $y-1$. We also add its quadratic term $RCI^2_{i,c,y-1}$ to investigate the potentioal non-linear relationship between land subsidy and entry probability. $Subsidy_{c,y-1}$ indicates the subsidy intensity of industrial land leasing in city c at year $y-1$. As discused in section 2.3, local governments compete for more complex industries by providing them with cheap industrial land. Low-price industrial land policy therefore offers a kind of subsidy which makes up for a lack of available knowledge and capabilities that are needed to branch into more complex industry space. Considering the incentive of attracting more complex industries, we also include the cross term of $Subsidy_{c,y-1}$ and $RCI_{i,c,y-1}$ ($Subsidy_{c,y-1} * RCI_{i,c,y-1}$) to examine the whether cities with higher land subsidy levels are more likely to gain more complex industries. δ_i, η_c and λ_y represent industry fixed effect, city fixed effects and year fixed effects respectively.

In addition to these key variables, we control for some city-specific variables ($X_{c,y-1}$) including: MPRICE which represents market land price and is measured by average land leasing price through bidding, auction and listing; ECI which represents Economic complexity of a city;PGDP which represents GDP per capita; PFDI which indicates foreign direct investment per capita;POPU which is the total population; and POPDEN which represents population density. These variables could capture the variations across cities in terms of their size, economic development level, openness, and agglomeration economies. Data used to calculate these variables are collected from the China City Statistic Yearbooks. The descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics of variables

Variable	Definition	Obs.	Mean	S.D.	Min	Max
ENTRY	The entry probability of new industries	39,268	0.033	0.178	0.000	1.000
DENSITY	Density of a specific industry i in city c	39,268	0.233	0.092	0.008	0.602
RCI	（ICI+1）/（ECI+1）	39,268	1.003	0.015	0.949	1.054
ICI	Industry complexity	696	0.006	0.015	-0.029	0.051
SUBSIDY	((Auction price – negotiation price)* leasing industrial area)/GDP	970	0.033	0.065	-0.017	1.045

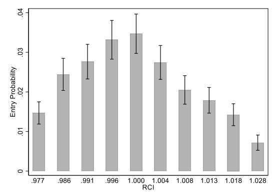
SUBSIDY2	Non-negotiation price – negotiation price (Yuan/m2)	1,061	398.036	528.937	-546.055	7392.882
DISTORTION	Distortion Index (Henderson et al., 2019)	266	0.436	0.215	0.037	1.625
ECI	Economic complexity of city	1,061	-0.002	0.008	-0.022	0.032
MPRICE	Auction Land Price(Yuan/m2)	1,061	529.850	550.125	3.371	7655.120
PGDP	GDP per capita (10000 Yuan)	970	1.537	1.998	0.189	29.536
PFDI	FDI per capita (1 Yuan)	937	72.440	184.195	0.000	2400.451
POPDEN	population density (1 person/Km2)	973	411.833	307.483	4.700	2661.540
POPU	Total population (10000)	973	423.167	298.509	16.370	3198.870

4 Empirical results

4.1 Exploratory analysis

Before proceeding to the regression results, we first describe the relationships between industrial diversification, complexity, and industrial land subsidy. Figure 3 displays the entry probability of a new industry in a given city for each decile of RCI. Obviously, the relationship between entry probability and RCI resembles an inverse U curve. The peak is at the fifth deciles (the decile closest to RCI=1), suggesting a city is more likely to enter new industries that have a level of complexity similar to that of the city itself. It could be expected that industries that have a much lower level of complexity than that of a given city are usually less competitive and could not bid for land and other resources to enter that city. Similarly, a given city is also less likely to gain the firms in those industries that are much more complex than its current industrial base because it usually lacks the required knowledge (embodied in the labor force, capital, management skills, and city governance quality) for the development of such industries.

We further explore graphically the heterogeneous effects of industrial land lease subsidy on the entry probability of industries with different deciles of RCI. Figure 4 reveals the difference in the mean entry probability of industries with different levels of industry complexity across cities with high (the top-third), medium(the medium-third) and low(the bottom-third) subsidy intensity (SUBSIDY). In general, for those cities that gain more complex industries (compared to their current industrial base), higher industrial land subsidy is associated with higher probability of gaining those industries. Although this is just a correlation, it might reflect city leaders' strategy of using industrial land subsidy to compete for more complex industries, and the outcome of this multi-city bidding process. Those cities that offer deeper subsidy eventually win those more complex industries.



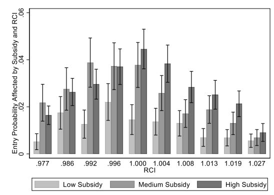


Figure 3. Entry probability by RCI **Figure 4. Entry probability by RCI and by levels of subsidy intensity**

(Note: The entry probability equals the ratio of the numbers of new developed industry （entry==1） to the numbers of industry that does not have RCA in the past 3 years)

4.2 Complexity and industrial diversification

Based on the results of the above exploratory analysis, we start by estimating the effect of complexity on the process of industrial diversification and then proceed to estimate the effect of industrial land subsidy as well as its effect on enhancing the complexity of a city's industry structure. Technically, we use the mean-centered dependent variables in our regression models so that the constant term represents the baseline expected probability of entry into the new industry (the intercept is equal to the mean of the dependent variable). Standard errors in all regression specifications are clustered at the city-industry level.

Table 2 shows the main result regarding the relationship between complexity and industrial diversification. Specifically, we can see that density plays a significantly positive role in increasing the entry probability of new industries in a city. In other words, industries that are more technologically related to the existing industries of a city are more likely to enter the city. This result is generally in line with the previous literature on relatedness and industrial diversification (Boschma and Capone, 2015; Balland et al., 2019; Guo & He., 2017; Zhu et al., 2017).

The coefficients of RCI square term (RCI_SQ) are negative in the simplest specification (Model 4). This result is quite stable after adding control variables and a variety of fixed effects (Model 5 to Model 6). This suggests that there is an inversed U curve relationship between the entry probability of an industry in a city and the land subsidy intensity. Based on the Model 4 to Model 6, the turning point is from 0.992 to 1.009, which is around 1 and in line with the above exploratory analysis. The inversed U curve relationship indicates that cities tend to diversify into industries that have similar levels of complexity with their current industries.

Table 2. The effect of complexity on industrial diversification

	Dependent variable: Entry(=1)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)

DENSITY	0.10428***	0.08426***	0.16328***		0.05617***	0.00980
	(0.01145)	(0.01918)	(0.03497)		(0.02072)	(0.04807)
RCI				43.40860***	35.58261***	83.60726***
				(6.89846)	(7.59258)	(18.37097)
RCI_SQ				-21.88544***	-17.82682***	-41.39889***
				(3.43834)	(3.78341)	(9.11006)
MPRICE		-0.00431**	0.00317		-0.00432**	0.00318
		(0.00193)	(0.00284)		(0.00193)	(0.00284)
KCI		2.12306***	2.81400***		2.18809***	3.74850***
		(0.28421)	(0.86559)		(0.30323)	(1.02784)
PGDP		-0.02854***	0.03752		-0.02846***	0.03404
		(0.00401)	(0.02784)		(0.00403)	(0.02791)
PFDI		-0.00022	-0.00061		-0.00003	0.00005
		(0.00115)	(0.00281)		(0.00115)	(0.00280)
POPDEN		-0.00000	0.00011		-0.00000	0.00014
		(0.00000)	(0.00011)		(0.00000)	(0.00011)
POPU		-0.00975***	-0.18312		-0.00847***	-0.21951
		(0.00200)	(0.15017)		(0.00204)	(0.15036)
Constant	0.03404***	0.03002***	-0.16088	0.03450***	0.02949***	-0.17626
	(0.00095)	(0.00124)	(0.19344)	(0.00109)	(0.00125)	(0.19477)
Observations	39,268	27,786	27,786	28,882	27,786	27,786
Year FE	No	No	Yes	No	No	Yes
City FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Adj R-squared	0.00219	0.00754	0.03131	0.00236	0.00823	0.03216

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0.1

4.3 The effect of land subsidy

Table 3 shows the effects of industrial land subsidy intensity on industrial diversification.

Model 1-3 shows the overall effects of industrial land subsidy intensity. In the baseline model (Model 1), the coefficient of subsidy intensity of industrial land leasing ($Subsidy$) is positive and significant and remains unchanged after adding industry-specific control variables and city-specific control variables (Model 2) and considering the fixed effects at both city and industry levels (Model 3).In the full Model 3, a 10% increase in subsidy intensity is associated with a 9% relative increase of the mean entry probability[7]. Overall, the result confirms that industrial land subsidy increases the entry probability of new industries and the effect is strong.

Model 4-6 shows the heterogeneous effects of industrial land subsidy on industries with different levels of complexity. When not controlling for anything else, we find that the interaction term ($Subsidy * RCI$) is significantly positive in Model 4, and this significantly positive effect remains stable after adding control variables (Model 5) and industry, city and year fixed effects (Model 6). Taking together, the results suggest that cities with higher industrial land lease subsidy density are more likely to attract industries with higher level of complexity.

We further replace the variable representing land subsidy intensity with two other variables. Table 4 show the effect of $Subsidy\ price\ gap(SUBSIDY2)$ defined in Equation (10) and land market distortion index (Henderson et al., 2019). In Table 4 (Column (1)-(2)), the interaction term ($SUBSIDY2 * RCI$) is significantly positive in all models, suggesting land subsidy is helpful in attracting new industries, especially for more complex industries. As shown in Table 4 (Column (3)-(4)), the coefficient interaction term $DISTORTION * RCI$ is significantly positive in the full Model (Column (4)) with control variables, city and industry fixed effects. These results further confirm that industrial land policy helps cities gain more complex industries.

[7] The unconditional probability of entry is around 3%. Since the Subsidy variable is log-transformed, a 10% increase in Subsidy is associated with 0.06853*log(1+10%)/0.03149=9%.

Table 3. The effects of land subsidy intensity

	Dependent variable: Entry(=1)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DENSITY		0.07772***	0.16955***		0.06610***	0.13694***
		(0.01963)	(0.03493)		(0.02023)	(0.03838)
RCI		-0.14590*	0.33039		-0.19274**	0.38956
		(0.08366)	(0.65851)		(0.08441)	(0.65975)
SUBSIDY	0.07578***	0.07275***	0.06853*	0.11131***	0.11143***	0.10794**
	(0.02057)	(0.02770)	(0.03902)	(0.02635)	(0.03522)	(0.04682)
SUBSIDY*RCI				3.55832**	3.32132*	3.43136*
				(1.61971)	(1.72789)	(1.93286)
MPRICE		-0.00804***	0.00083		-0.00871***	0.00059
		(0.00215)	(0.00299)		(0.00219)	(0.00300)
KCI		1.72265***	2.94522***		1.70215***	3.11928***
		(0.30719)	(1.01391)		(0.30707)	(1.01177)
PGDP		-0.02715***	0.03994		-0.02680***	0.04043
		(0.00406)	(0.02791)		(0.00407)	(0.02791)
PFDI		-0.00007	-0.00052		-0.00014	-0.00027
		(0.00115)	(0.00281)		(0.00115)	(0.00281)
POPDEN		-0.00000	0.00009		-0.00000	0.00010
		(0.00000)	(0.00011)		(0.00000)	(0.00011)
POPU		-0.00791***	-0.15521		-0.00756***	-0.16993
		(0.00204)	(0.14990)		(0.00205)	(0.14975)
Constant	0.03328***	0.03012***	-0.11826	0.03385***	0.03055***	-0.13586
	(0.00108)	(0.00124)	(0.19435)	(0.00113)	(0.00127)	(0.19421)
Observations	28,431	27,786	27,786	28,431	27,786	27,786
Year FE	No	No	Yes	No	No	Yes
City FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Adj R-squared	0.00089	0.00806	0.03143	0.00127	0.00835	0.03167

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0. 01

Table 4 The effect of subsidy attractiveness and distortion index

	Dependent variable: Entry(=1)			
	Subsidy Price Gap (SUBSIDY2)		Land Distortion Index (DISTORTION)	
VARIABLES	(1)	(2)	(3)	(4)
DENSITY	0.06961***	0.13679***	0.08151***	0.13418***
	(0.02030)	(0.03881)	(0.02062)	(0.03864)
RCI	-0.17698**	0.09567	-0.13708	0.31149
	(0.08687)	(0.67733)	(0.08413)	(0.66795)
SUBSIDY2	0.00121	0.00291		
	(0.00232)	(0.00318)		
SUBSIDY2*RCI	0.23454***	0.20662**		
	(0.06817)	(0.08181)		
DISTORTION			0.00170**	0.16806
			(0.00071)	(0.10671)
DISTORTION *RCI			0.04614	0.09766*
			(0.04041)	(0.05220)
MPRICE	-0.00693*	-0.00197	-0.00474**	0.00439
	(0.00390)	(0.00605)	(0.00201)	(0.00288)
KCI	2.07238***	2.62048**	1.85940***	3.33154***
	(0.30305)	(1.04077)	(0.31625)	(1.03143)
PGDP	-0.02630***	0.03591	-0.03214***	0.03588
	(0.00412)	(0.02813)	(0.00422)	(0.02905)
PFDI	-0.00036	-0.00011	0.00016	-0.00057
	(0.00119)	(0.00282)	(0.00120)	(0.00290)
POPDEN	-0.00000	0.00014	-0.00000	0.00015
	(0.00000)	(0.00011)	(0.00000)	(0.00011)
POPU	-0.00918***	-0.21712	-0.00927***	-0.23709
	(0.00207)	(0.15175)	(0.00210)	(0.15428)
Constant	0.03106***	-0.20517	0.03052***	0.05637
	(0.00130)	(0.19714)	(0.00130)	(0.04517)
Observations	26,884	26,884	27,103	27,103
City FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Adj R-squared	No	Yes	No	Yes
Observations	0.00820	0.03230	0.00808	0.03218

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0.1.

4.4 Robustness Checks

4.4.1 Group regression and different dependent variable

We check the robustness of our empirical results from several perspectives. First, we estimate separate models to reveal the effects of industrial land subsidy on the entry probability of industries with different levels of complexity. In doing so, we divide the sample into 2 groups based on the value of RCI: less complex group in RCI (RCI<=1), and more complex group (RCI>1). The results for each subgroup are shown in Table 5. In the baseline models without fixed effects, the coefficient of subsidy intensity ($SUBSIDY$) is significantly positive for more complex group but is insignificant for less complexity group. Specifically, a 10% increase in land subsidy intensity is associated with 26% increase in entry probability in more complex group. After adding fixed effects at the city, year and industry levels, the coefficient of subsidy intensity remains significantly positive for the group with the higher level of RCI. This result is generally in line with our previous findings.

Second, we use a stricter definition of RCA. The value of RCA equals one only when the location quotient (LQ) is larger than 2 and reproduce Table 4. The result is shown in Table 6 (Column (1)-(2)). The coefficient of $SUBSIDY$ and interaction term ($SUBSIDY * RCI$) is significantly positive in Model 1 and Model 2, suggesting that cities with higher subsidies are more likely to attract more complex industries.

Third, considering the endogeneity between density and entry probability, we further use the output and the output growth of each industry in each city as the dependent variable to check the robustness of our results. The results are shown in Table 6 (Column (3)-(6)). For the absolute output (Column (3)-(4)), subsidy has a positive effect and the interaction term ($SUBSIDY * RCI$) is significantly positive in Model 3. In Column (5)-(6), we can find that subsidy can stimulate the growth of output in the baseline model and the model with controls and fixed effects. The interaction term ($SUBSIDY * RCI$) is significantly positive in the full Model (Model 6). Overall, these results provide additional evidence that industrial land policy mainly fosters the growth of more complex industries.

Table 5. The heterogeneous effects of land subsidy sub-sample regressions

	Dependent variable: Entry(=1)			
	(1)	(2)	(3)	(4)
VARIABLES	Less complex	More complex	Less complex	More complex
DENSITY	0.04333	0.11986***	-0.01433	0.01695
	(0.03188)	(0.02617)	(0.07107)	(0.07620)
MPRICE	-0.01223***	-0.00620**	0.00386	-0.00142
	(0.00374)	(0.00264)	(0.00573)	(0.00333)
SUBSIDY	0.03777	0.19217***	-0.01368	0.22651***
	(0.03268)	(0.05799)	(0.04638)	(0.08571)
KCI	2.41603***	0.37300	0.91843	-1.00700
	(0.43109)	(0.41168)	(1.28464)	(1.25811)
PGDP	-0.02499***	-0.02690***	0.03340	0.06706*
	(0.00662)	(0.00524)	(0.04137)	(0.03625)
PFDI	-0.00177	0.00083	-0.00369	0.00144
	(0.00216)	(0.00132)	(0.00598)	(0.00294)
POPDEN	-0.00001	0.00001	-0.00009	0.00013
	(0.00001)	(0.00001)	(0.00017)	(0.00012)
POPU	-0.00533	-0.00881***	0.11104	-0.25404
	(0.00361)	(0.00236)	(0.24593)	(0.17397)
Constant	0.03309***	0.02945***	0.18183	-0.29972
	(0.00226)	(0.00168)	(0.31871)	(0.22523)
Observations	11,837	15,949	11,837	15,949
Year FE	No	No	Yes	Yes
City FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Adj R-squared	0.00775	0.00832	0.06463	0.04112

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0.1

Table 6 Robustness check by using different dependent variables

Dependent variable:	Entry(=1) (RCA=1 if LQ>2)		Log(Output)		Output growth	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DENSITY	0.06996***	0.16104***	2.23698***	4.70454***	-0.14111***	-0.37730***
	(0.01099)	(0.02014)	(0.06627)	(0.10446)	(0.01539)	(0.02816)
RCI	-0.21853***	0.93498**	-5.97958***	3.13959***	0.20675***	-1.15525
	(0.04934)	(0.41217)	(0.37504)	(0.71649)	(0.07756)	(0.80742)
SUBSIDY	0.04444**	0.05743**	0.24465***	0.47233***	0.01002	0.18383***
	(0.01926)	(0.02494)	(0.07701)	(0.04560)	(0.02440)	(0.03189)
SUBSIDY*RCI	2.37345***	1.58619**	45.68342***	5.97511	0.08852	4.81286***
	(0.68978)	(0.77489)	(4.18573)	(3.96354)	(1.16135)	(1.27651)
MPRICE	-0.00512***	-0.00293	0.00330	-0.01435***	0.00366	-0.00426
	(0.00137)	(0.00199)	(0.00708)	(0.00337)	(0.00246)	(0.00409)
KCI	0.55000***	2.12426***	-6.17606***	10.32875***	3.64473***	6.21714***
	(0.18435)	(0.62709)	(1.07562)	(1.06960)	(0.26567)	(1.20310)
PGDP	-0.00975***	0.01161	-0.14759***	-0.02620	-0.00457	0.01894
	(0.00244)	(0.01630)	(0.01736)	(0.02992)	(0.00415)	(0.02901)
PFDI	-0.00155**	0.00094	-0.04323***	-0.00552*	0.00077	-0.01343***
	(0.00073)	(0.00176)	(0.00488)	(0.00316)	(0.00120)	(0.00353)
POPDEN	-0.00000	0.00005	-0.00002	0.00025**	-0.00001*	-0.00000
	(0.00000)	(0.00006)	(0.00002)	(0.00011)	(0.00000)	(0.00013)
POPU	-0.00596***	-0.07599	-0.19145***	-0.48544***	0.01581***	-0.08417
	(0.00123)	(0.07934)	(0.00902)	(0.16191)	(0.00200)	(0.18676)
Constant	0.01548***	0.01569	0.74828***	1.23718***	-0.02224***	-0.26188
	(0.00072)	(0.11409)	(0.00527)	(0.30086)	(0.00111)	(0.24818)
Observations	39,520	39,520	58,277	58,277	58,277	58,277
Year FE	No	Yes	No	Yes	No	Yes
City FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Adj R-squared	0.00576	0.02263	0.10089	0.25187	0.00955	0.03240

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0.1.

4.4.2 Instrumental Variable (IV) approach

In the above subsection (and Table 6) we address the potential endogeneity between relatedness (DENSITY) and entry probability (RCA). There might be another type of endogeneity coming from the unobserved variables which influence both land subsidy intensity and our outcomes (entry probability, output, etc.) simultaneously. One example of this type of endogeneity is that, if Chinese city governments want to attract more complex industries and boost the local economy, they might implement both land subsidy policy and other preferential policies together. Therefore, those other policies are correlated with the land subsidy policy and will also affect industries' entry probability and output, but we are unable to observe all of those policies. Such an endogeneity problem might bias our estimate of land subsidy policy's effect.

To mitigate this type of endogeneity, as a robustness check, we employ the Instrumental Variables (IV) approach to estimate our main model. We need to seek for the instrumental variables that are correlated with land subsidy but uncorrelated with other possible preferential policies. In other words, the instrumental variables should only influence our outcomes through the land subsidy channel (exclusion restriction). To meet this requirement, we select two IVs. One is the land suitability index (*SUITABILITY*), which comes from Global Agro-Ecological Zones database (http://www.fao.org/nr/gaez/en/) and measures how suitable the agricultural land around a city is for farming. The higher this index is, the higher opportunity cost the city bears if it leases it out at very low prices, and thus will reduce a city's land subsidy intensity. The other variable is the ratio of a city's planned construction area to its agricultural area (*PLAN_AREA)* as a mandatory requirement specified in China's long-term Land Use Planning. Chinese central government uses this mandatory requirement to prevent city governments from excessively expanding urban construction land, with the purpose of ensure food security. The smaller this ration is, the harder the city can expand its urban construction land and lease it out. These two variables are both exogenous to city governments' behaviors and can only work through the land supply channel to influence our outcome variables.

The results based on this IV approach are shown in Table 7. For the first-stage, in Column (1), the coefficient of *SUITABILITY* is significantly negative and the coefficient of *PLAN_AREA* is significantly positive, which is consistent with our expectation that higher suitability with higher opportunity cost will lower the subsidy intensity, and less planed area will increase the difficulty in leasing more land out and reduce the subsidy intensity. For the weak instrument identification test, F-statistic for the first stage is larger than 10. The Hansen J statistic for over identification test is 0.426 (P-value is 0.773), suggesting we cannot refuse the hypothesis that all instrument variables are exogenous. For the second-stage, the coefficient of $SUBSIDY$ is positive and significant, which confirms that industrial land subsidy increases the entry probability of new industries. Since both of the instrument variables are time-invariant in our sample period, we cannot include fixed effects. Since only 90 cities have the data of both instrument variables, our sample size shrinks.

In Column (2), we use *SUITABILITY*, *PLAN_AREA*, and the interactions of them with *RCI* to instrument for *SUBSIDY* and *SUBSIDY*RCI*. In the estimation of *SUBSIDY* in the first stage, the coefficient of *SUITABILITY* is significantly negative and the coefficient of *PLAN_AREA* is significantly positive. In the estimation of *SUBSIDY*RCI* in the first stage, the coefficient of *SUITABILITY*RCI* is significantly negative and the coefficient of *PLAN_AREA and PLAN_AREA*RCI* is significantly positive. The F statistic in the first stage suggests the instruments are not weak. The Hansen J statistic for over identification test indicates we cannot refuse the null hypothesis. We find that the interaction term ($SUBSIDY * RCI$) is significantly positive (with a larger size), which is consistent with the OLS results. This result strengthens our finding that cities with higher industrial land lease subsidy are more likely to obtain more complex industries.

Table 7 Robustness check by adopting an IV approach

	Dependent variable: Entry(=1)	
VARIABLES	(1)	(2)
SUBSIDY	2.49962**	1.81395*
	(1.12565)	(0.93924)
SUBSIDY*RCI		26.47803***
		(8.14406)
DENSITY	0.10381***	0.03211
	(0.03873)	(0.04901)
RCI	-0.13130	-0.29428*
	(0.14558)	(0.15015)
MPRICE	-0.05856*	-0.03776
	(0.03009)	(0.02461)
KCI	-3.62500	-1.64963
	(2.22272)	(1.77679)
PGDP	-0.07892***	-0.05810***
	(0.02362)	(0.01869)
PFDI	-0.00470*	-0.00612***
	(0.00245)	(0.00232)
POPDEN	0.00001	0.00001
	(0.00001)	(0.00001)
POPU	0.02680	0.01000
	(0.02226)	(0.01793)
Constant	0.02884***	0.03404***
	(0.00238)	(0.00280)
Observations	9,765	9,765
Over Identification Test	0.426	0.515
(Hansen J statistic)	(0.7731)	(0.5141)

First Stage for Column(1):

$$\begin{aligned}\mathrm{SUBSIDY} = {} & -0.00015^{***} * \mathrm{SUITABILITY} + 0.00008^{***} * \mathrm{PLANAREA} + 0.01906^{***} * \mathrm{DENSITY} \\ & - 0.00825 * \mathrm{RCI} + 0.02568^{***} * \mathrm{MPRICE} + 1.83072^{***} * \mathrm{KCI} + 0.01435^{***} * \mathrm{PGDP} \\ & - 0.00053 * \mathrm{PFDI} + 0.00001^{**} * \mathrm{POPDEN} - 0.02182^{***} * \mathrm{POPU} + 0.00002\end{aligned}$$

F test of excluded instruments(SUITABILITY, PLAN_AREA): F= 14.87

First Stage for Column(2):

$$\begin{aligned}SUBSIDY = {} & -0.00018^{***} * \mathrm{SUITABILITY} + 0.00008^{***} * \mathrm{PLAN\_AREA} + 0.00895^{***} * \mathrm{SUITABILITY} \\ & * \mathrm{RCI} - 0.00218^{***} * \mathrm{PLAN\_AREA} * \mathrm{RCI} + 0.02809^{***} * \mathrm{DENSITY} + 0\,.00534 * \mathrm{RCI} \\ & + 0\,.02561^{***} * \mathrm{MPRICE} + 1.75593^{***} * \mathrm{KCI} + 0.01410^{***} * \mathrm{PGDP} - 0.00061 \\ & * \mathrm{PFDI} + 0.00001^{***} * \mathrm{POPDEN} - 0.02215^{***} * \mathrm{POPU} - 0.00025\end{aligned}$$

F test of excluded instruments (SUITABILITY, PLAN_AREA, SUITABILITY*RCI, PLAN_AREA*RCI): F= 16.28

$$\begin{aligned}\mathrm{SUBSIDY} * \mathrm{RCI} = {} & -0.00000 * \mathrm{SUITABILITY} + 0.00000^{***} * \mathrm{PLAN\_AREA} - 0.00119^{***} \\ & * \mathrm{SUITABILITY} * \mathrm{RCI} + 0.00028^{***} * \mathrm{PLAN\_AREA} * \mathrm{RCI} + 0.00200^{***} * \mathrm{DENSITY} \\ & + 0\,.00422^{***} * \mathrm{RCI} - 0.00011^{***} * \mathrm{MPRICE} - 0.01709^{***} * \mathrm{KCI} - 0.00039^{***} \\ & * \mathrm{PGDP} + 0.00005^{***} * \mathrm{PFDI} - 0.00000 * \mathrm{POPDEN} + 0.00011^{***} * \mathrm{POPU} \\ & - 0.00016^{***}\end{aligned}$$

F test of excluded instruments (SUITABILITY, PLAN_AREA, SUITABILITY*RCI, PLAN_AREA*RCI): F = 198.12

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusion

Drawing upon the recent literature on relatedness, industrial diversification, and economic complexity, this study investigates whether industrial land policy in China can help cities branch into new and more complex economic activities. Our empirical results show that cities are more likely to branch into new industries that have similar levels of complexity to their current base, and cities that provide higher industrial land lease subsidy are more likely to attract more complex industries.

The findings of this study have clear policy implications. Without any interventions, regions are less likely to branch into more complex industries. Developed regions that start from the core areas of the industry space have more opportunities to jump to more complex new industries and sustain a faster economic growth than developing regions that only branch into peripheral industries. Such an empirical regularity is constraints developing regions since their industrial diversification is confined by the complexity of their existing industries. With properly-designed policy interventions (e.g., providing land subsidies to more complex industries), cities might be able to attract those industries, which further enhances the potential for industrial upgrading and economic growth. In addition, our major findings are also of significance for firms– how to choose a city with both matching industrial structure and suitable industrial policies to maximize their growth potential.

However, such a land subsidy policy widely used by Chinese city governments also has its cost and potential risk. Deep subsidy to industrial land might cause resource misallocation along two dimensions. First, cities that lease out a vast amount of industrial land will have a constrained residential land supply, which will raise housing prices and hurt residents' welfare. So industrial land policy and housing policy should go hand and hand. Second, if city governments use land subsidy to target the "wrong" industries (with very low level of relatedness or the complexity level is too high compared to the current industrial base), opportunity costs will be very high and it will create misallocation of scarce resources. Quantifying such misallocation cost and associated risk is beyond our paper, but it will be a promising future research direction to evaluate both the benefit of the cost of such an industrial land subsidy policy.

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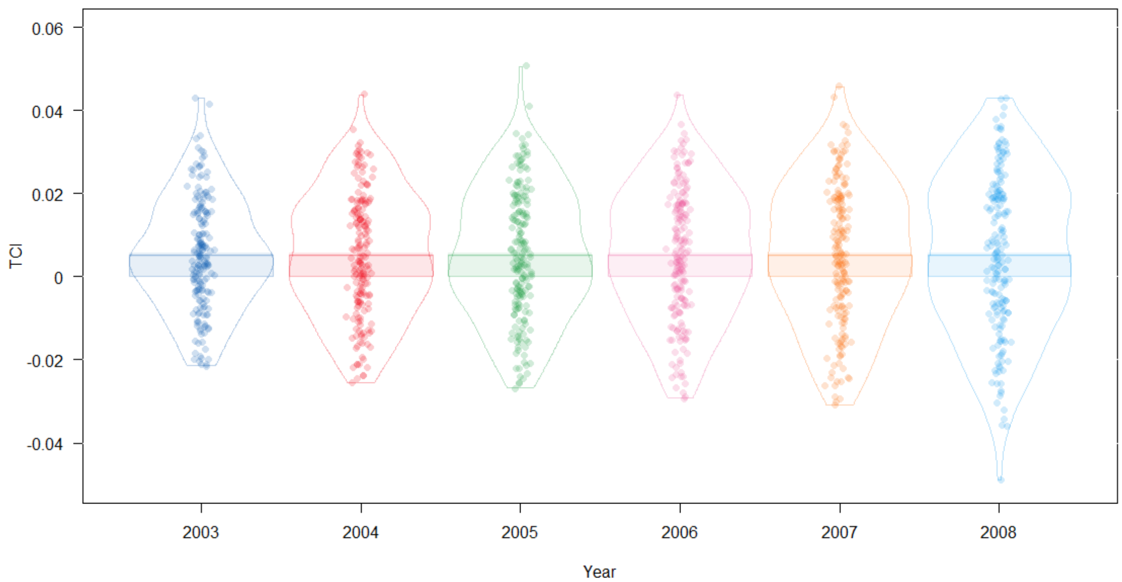
Appendix

A1 The effect of land subsidy: Probit model result

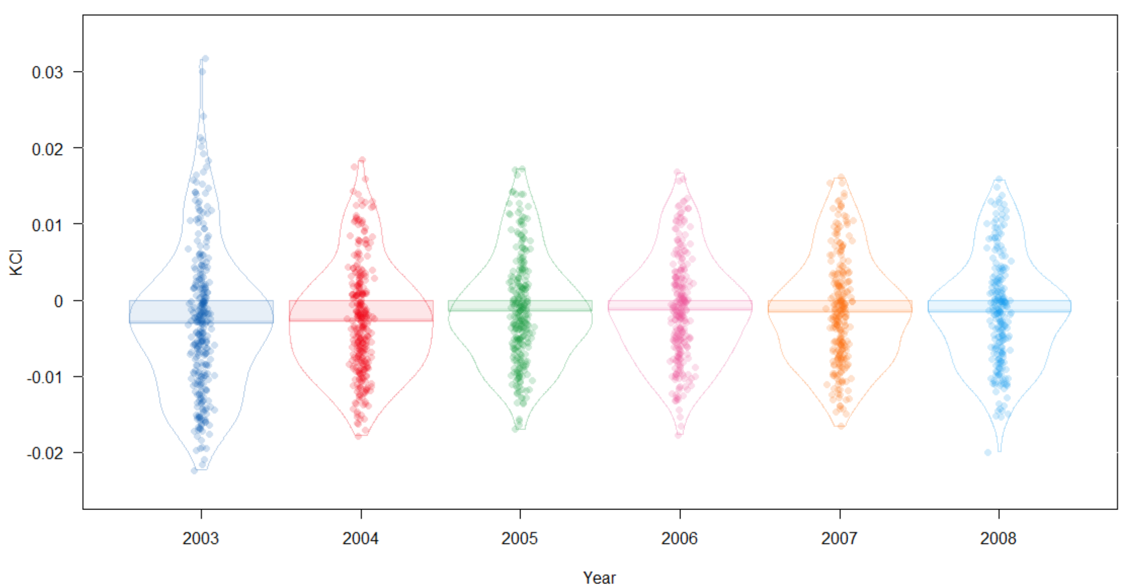
	Dependent variable: Entry(=1)					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DENSITY		1.24355***	3.25922***		1.13576***	2.98881***
		(0.23143)	(0.45114)		(0.23630)	(0.47179)
RCI		-2.28075**	5.04946		-2.85880**	5.50125
		(1.12564)	(8.03401)		(1.15218)	(8.04282)
SUBSIDY	0.77782***	0.72133***	0.47995	1.09276***	1.03252***	0.75714*
	(0.16989)	(0.23001)	(0.41895)	(0.19720)	(0.26439)	(0.44196)
SUBSIDY*RCI				32.70672**	28.01774*	26.23904*
				(14.31569)	(14.51605)	(15.10991)
MPRICE		-0.08440***	0.02201		-0.08929***	0.02310
		(0.02556)	(0.05041)		(0.02560)	(0.05045)
KCI		22.32553***	35.98277***		21.92341***	37.85741***
		(3.44743)	(12.49495)		(3.42187)	(12.50603)
PGDP		-0.45011***	0.02202		-0.44541***	0.04098
		(0.06761)	(0.42328)		(0.06728)	(0.42293)
PFDI		0.00789	-0.00975		0.00792	-0.00611
		(0.01667)	(0.04515)		(0.01663)	(0.04512)
POPDEN		0.00001	0.00091		0.00002	0.00109
		(0.00005)	(0.00182)		(0.00005)	(0.00182)
POPU		-0.11779***	-2.34001		-0.11524***	-2.59422
		(0.03024)	(2.63777)		(0.03032)	(2.64569)
Constant	-1.83577***	-1.92516***	-1.87382***	-1.83148***	-1.92166***	-1.86207***
	(0.01469)	(0.01902)	(0.56550)	(0.01487)	(0.01909)	(0.56782)
Year FE	28,431	27,786	27,786	28,431	27,786	27,786
City FE	No	No	Yes	No	No	Yes
Industry FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Pseudo R-squared	0.00252	0.02896	0.12547	0.00350	0.02962	0.12590

Note: All independent variables are mean-centered and lagged by one period; Robust standard errors are in parentheses and are clustered at the city and industry level; *** p<0.01, ** p<0.05, * p<0. 01.

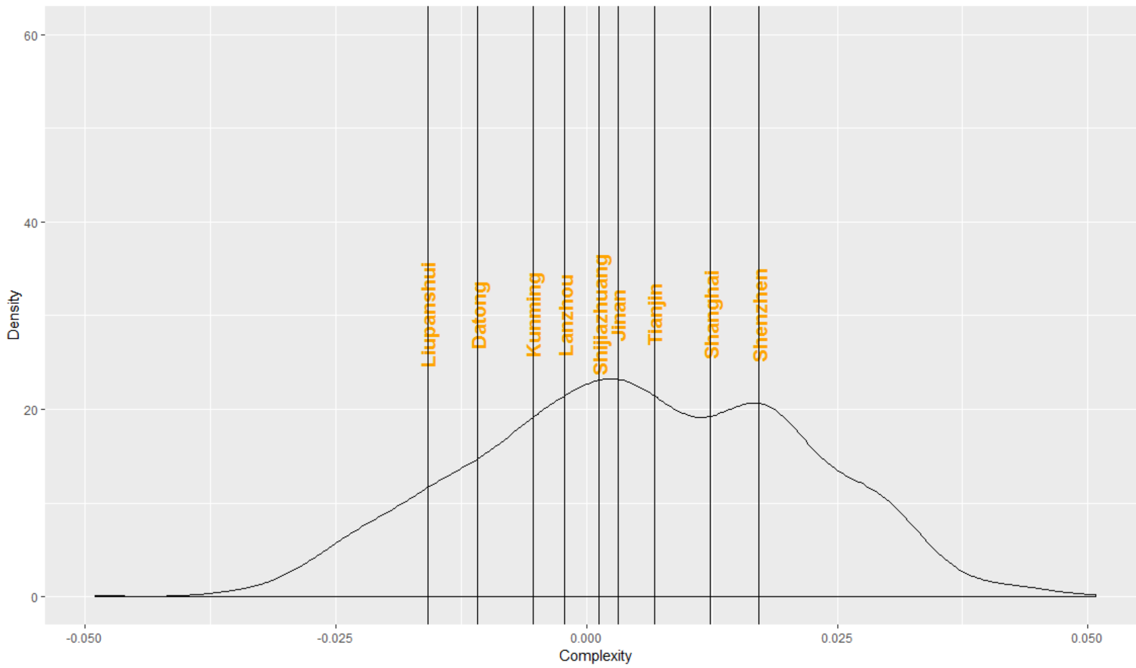
A2.City-level Complexity Distribution during 2003-2008



A3.Industrial-level Complexity during 2003-2008



A4.Industry complexity distribution and city complexity examples



A5. City complexity distribution and industry complexity examples