Building Tall, Falling Short: An Empirical Assessment of Chinese Skyscrapers

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Abstract

This article examines the determinants and economic efficiency of construction-led urbanization in China, focusing on skyscraper development as a prominent example. As the emerging leader in skyscraper construction, China accounts for 60% of all high-rises built around the world since 2000. Employing a political economy lens, we find that local governments provide developers with significant discounts on land prices in non-central locations by manipulating land auctions in an attempt to encourage the development of new urban agglomerations, particularly in cities where local leaders are motivated by stronger career incentives and during the central government's monetary easing policy period. However, 5 to 10 years after their completion, these subsidized skyscrapers yield few spatial spillovers in the form of a land price premium, new business formation, or endogenous urban amenities, in contrast to the substantial positive spillovers near unsubsidized skyscrapers. The lack of spillover effects is caused by a combination of poor location, less reliable developers, and inadequate supporting infrastructure, calling into question the effectiveness of state-engineered urban development.

Keywords: Skyscrapers, government subsidy, spillovers, land value, misallocation, China

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1 Introduction

The rapid urbanization of China over the past four decades has been nothing short of remarkable. Between 2000 and 2019, the country's urban population share skyrocketed from 36.2% to 60.6%. A distinctive feature of China's urbanization is that population growth is accompanied, if not preceded, by an equally remarkable process of building and infrastructure development, which sets the country apart from many other developing countries, where urban build-up and infrastructure supply often fail to keep pace with surging population growth. Perhaps one of the most illustrative examples is its recent skyscraper construction boom: 1,575 skyscrapers have been constructed in China since 2000, accounting for an astonishing 60% of the world's new tall buildings, even outpacing the high-rise boom in America in the early 20^{th} century.

A crucial driver of China's urban development is the strong incentives for subnational officials to promote major urban projects. Under the belief that providing modern transportation systems and state-of-the-art buildings will bring investments and businesses to their cities, local officials use their control of key resources, such as land, to encourage the development of mega-projects. The perceived benefits for them are two-fold: first, as the best symbolization of local economic achievement, these new landmarks could enhance the city officials' promotion prospects within the country's political hierarchy (Chen and Kung, 2016, Wang et al., 2020); and second, these structures can potentially increase local land prices, and land sale revenues have accounted for an increasingly large proportion of the income of subnational governments since the 1994 tax recentralization reform (Xu, 2011). These incentives further increased following the 2008 Financial Crisis and the Chinese government's "four-trillion" plan, which directed massive amounts of money to infrastructure and real estate projects in an effort to stimulate the economy (Chen et al., 2020). However, this belief rests largely on the notion that state-led urban development projects generate economic spillovers sufficient to justify their costs. There have been few attempts to comprehensively evaluate how local governments subsidize these projects, and whether the spillover effects of *subsidized* projects effectively offset their costs.

Our paper seeks to fill this gap by assessing the determinants and economic impacts of a prime example of state-led urbanization—the massive construction of skyscrapers in China. We start by documenting two spatial patterns of skyscraper development in China. First, about 69.2% of skyscrapers are located in small or mid-sized cities, some of which even fall at the bottom of the GDP distribution. Second, compared with residential skyscrapers, commercial high-rises tend to be located farther away from the central business district (CBD), and their heights are also less responsive to land costs. Both patterns appear to contradict the neo-classical theory that skyscrapers exemplify land–capital substitution. Instead, various official policy documents provide anecdotal evidence of a "visible hand" explanation in which local governments drive these projects. Officials in some regions are highly motivated to promote high-end service agglomeration by subsidizing high-rise commercial centers—often in new towns on the urban periphery—perhaps an alternative growth strategy as opposed to a traditional industry-fueled approach.[1] Subsidies in the form of land parcel discounts are among the most common policy instruments used to support vertical expansion in cities.

We begin our empirical analysis by first providing compelling evidence that commercial skyscrapers have been subsidized. Guided by insights from policy documents, we use the price discounts on land parcels that city governments have granted to developers for skyscraper construction as a proxy for subsidies to these projects. Local governments, as the sole suppliers of land, typically exploit their discretionary power over the allocation of urban land, manipulating transaction prices to influence developers' location choices in an attempt to fulfill their urban development plans (Wang et al., 2020). By matching land transaction records from 2003 to 2017 to the universe of skyscrapers constructed in China between 2006 and 2014, we infer the magnitude of these discounts by noting the price difference

[1] This incentive has not been extended to residential skyscrapers, as they presumably generate fewer agglomeration effects.

between land parcels used to build commercial skyscrapers and nearby plots with similar observable characteristics, which can be assumed to have had a comparable market value. We confirm that the land price discounts granted to commercial skyscraper projects are sizable—about 40.1% of the average transaction price. Reassuringly, our placebo group (residential skyscrapers) received no such discount. Further evidence reveals that such discounts are handed over in restrictive auctions with low reserve prices and strict developer qualification requirements, which usually end up with only one eligible bidder who wins the plot at the reserve price.

We also present a set of heterogeneity analyses that shed light on the political factors behind subsidized skyscraper development. The price discounts for skyscrapers are positively associated with both the career incentives of city mayors (proxied by their estimated likelihoods of promotion) and the central government's 4 trillion RMB stimulus plan. However, the land discounts are not significantly greater in regions with land corruption records, nor do they seem to be disproportionately directed to developers with a background prone to collude with local government.

Next, we evaluate the economic returns of these subsidized commercial skyscraper projects—particularly whether these subsidies pay off in the future by generating considerable positive spatial spillovers. We consider changes in three outcomes upon completion of the skyscraper: nearby land prices, the number of new firms registered, and the number of nearby endogenous amenities. To identify the spillover effects, we exploit a spatial difference-in-differences (DID) research design that compares the change in land prices in neighboring areas (within a 2km radius of a newly built skyscraper) at the time the skyscraper is completed with the change in land prices in areas slightly farther away (a 2–3km radius).[2] Although neither the temporal nor the spatial variations (i.e., when the skyscraper was completed and its location) were completely random, our DID estimate would be unbiased unless time-varying endogenous factors that coincided with commercial skyscraper completion also varied sharply

[2] We ran a set of ring analyses that helped us choose the bandwidth of the treatment and control rings.

within a narrow radius around the new skyscrapers. To ensure that this is not the case, we control for a host of parcel characteristics and amenity variables, and flexibly include the time trend–interacted coordinate differences between the nearby parcel and the commercial skyscraper.

Our estimates show that commercial skyscrapers generate very localized spillover effects, merely by increasing the land value, the number of new firms, and the local business amenities within a 2km radius of the skyscrapers. More importantly, these very localized spatial spillovers measured using either proxy almost exclusively occur around *unsubsidized* commercial skyscrapers. Using an event study approach, we find no differential pre-trends in the main outcomes, which supports our identification assumptions. The trends in land value and registered firms near subsidized and unsubsidized skyscrapers begin to diverge quickly after the projects' completion, with no significant effects detected near subsidized skyscrapers after 5 to 10 years. Moving beyond the local effects, city-level analysis confirms that skyscrapers do not confer short- or long-term benefits on the wider region. To ensure the robustness of our DID estimations, we conduct a battery of falsification tests. We rule out alternative explanations such as supply responses. A spatial randomization inference test with counterfactual locations selected at random from within a 5km radius of a skyscraper's site demonstrates that the results are not spurious.

We provide further evidence on the underlying mechanisms behind the lack of spillover around subsidized projects. By and large, spillover effects are highly dependent on location: high-rises in central locations with high productivity and availability of amenities accommodate the strong demand for space, and thus create substantial agglomeration benefits. In contrast, skyscraper projects in smaller cities and non-central locations where space is not in limited supply fail to achieve the intended positive spillovers. Apart from the ill-chosen locations of subsidized skyscrapers, the poor development of these real estate projects also plays a role: subsidized skyscraper projects are more often run by developers with a higher risk of capital-chain rupture, and a slower construction process.

Skyscrapers are among the most durable types of structures. This is a double-edged sword: it makes poor location decisions extra costly but also produces expectations of positive returns that may materialize in the long run through sustained urbanization and the continued promotion of new agglomerates. We are, however, less optimistic about such prospects for two reasons. First, in the long term, the potential for urbanization in China may be constrained by future demographic shifts. Second, we find that supporting public investments near subsidized skyscrapers lag behind those near unsubsidized ones. The supply of public land parcels for transit projects and other public amenities does not significantly increase beyond 5 years after building completion near subsidized skyscrapers, unlike the immediate positive and sustained growth in supply near unsubsidized ones.

In addition, there are growing concerns about the short-term financial burdens these projects place on developers and municipal finances. While developers struggle to complete their skyscrapers without sustained government support, their projects fail to create a cascade of land revenue, which may exacerbate the strain on local municipal finances. This possibility has contributed to concerns about an impending local-government debt crisis.

This paper contributes to two strands of the literature. First, it advances the burgeoning literature on vertical urban structure.[3] Concerning the determinants of skyscraper development, some researchers consider it an outcome of supply-side land–capital substitution, that is, the substitution of expensive land with height (Barr, 2010; Ahlfeldt and McMillen, 2018; Barr and Luo, 2021). Going beyond economic fundamentals, an alternative explanation attributes rising skylines to a "beauty contest" between builders (Helsley and Strange, 2008; Barr, 2012; Barr, 2013; Lu, 2023). Our study takes a political economy approach to identify the drivers of skyscraper development in China, providing quantitative evidence of government intervention and underlying political incentives.[4]

[3] Ahlfeldt and Barr (2022) recently reviewed the "skyscraper economics" literature.

[4] One related paper Gjerløw and Knutsen (2019), which show in a cross-country study that autocracies systematically build more skyscrapers than democracies, potentially due to vanity or a lack of accountability.

Regarding the economic impacts of skyscrapers and the broader benefits they might generate, a small strand of research (Koster et al., 2014; Liu et al., 2018, 2020) has investigated within-building agglomeration economies by examining vertical rent gradients and firm sorting in tall buildings. Curci (2020) explores the effect of city-level building heights on firm agglomeration, productivity and overall urban structure among U.S. cities. Our paper adds to this literature by studying the spillover effects around tall buildings in China, the country with the largest number of skyscrapers in the world, and thus greatly enriches the geographical profile of related studies. To the best of our knowledge, this paper is among the first empirical studies to estimate the local spillover effects around tall buildings. Moreover, China's fine variation in skyscraper construction over time and across cities presents a unique test case for assessing the heterogeneous impact of skyscrapers.

Secondly, our paper relates to the literature on the political economy of public investments. Previous work has examined the impacts of legislative representation and electoral incentives on the allocation of centrally-provided local public projects (Knight, 2004; Alok and Ayyagari, 2020). Our focus is instead on local governments' incentives and measures to shape the placement of skyscraper projects in a non-electoral setting. This paper also resonates with other studies on the role of local governments in China's urbanization process. Scholars have suggested that political centralization and economic regional decentralization incentivize local leaders to engage in tournament competition by strategically leveraging the resources under their control to attract investments and boost growth (Xu, 2011; Yu et al., 2016). It has been shown that the career incentives of local officials distort land allocation, leading to "image projects" (Chen and Kung, 2016), urban sprawl (Wang et al., 2020), and efficiency losses (Henderson et al., 2022). In our context, skyscrapers are both highly visible and thought to generate spillovers, and consequently are favored by local officials with strong career incentives. They are, however, also expensive and durable, which makes their misplacement very costly. We provide suggestive evidence that heavily subsidized skyscrapers built in less prime locations yield far fewer spillovers than expected, informing a heated debate about the effectiveness of such state-orchestrated urbanization drives.

The remainder of the paper is organized as follows. Section 2 introduces the data. Section 3 presents the spatial pattern of Chinese skyscraper construction and quantifies how local governments intervene in commercial skyscraper development. Section 4 evaluates the economic returns of commercial skyscrapers. Section 5 discusses several potential mechanisms as well as the implications of our findings. Section 6 concludes.

2 Data

We compile multiple data sources to study Chinese skyscrapers, including global skyscraper databases, Chinese land transaction records, and data on firm registration, business amenities and infrastructure. In this section, we provide a detailed description of each source. Summary statistics of the relevant variables are presented in Table 1.

Skyscraper Data We obtain data on skyscraper development from Emporis.com and the Council on Tall Buildings and Urban Habitat (CTBUH). They contain the most comprehensive information on skyscrapers in China and in the rest of the world, and their data cover over 40 years (Jedwab et al., 2022). According to the CTBUH, they rely on over 2 million members from more than 100 countries (including building owners, developers, urban planners, architects, financiers, engineers, contractors and suppliers) to build and maintain the database. The two sources of data are suited to the study of skyscrapers and have been commonly used in the literature (see, for example, Barr, 2013; Ahlfeldt and McMillen, 2018; Ahlfeldt and Pietrostefani, 2019; Barr and Luo, 2021; Jedwab et al., 2022).

We then extract the information on Chinese skyscrapers—buildings with a fixed height of more than 100m[5] that were completed between 2006 and 2014. With detailed information on their height, specific use (commercial or residential), completion time, developer(s),

[5] China's "Uniform Standard for Design of Civil Buildings" issued by the Ministry of Housing and Urban–Rural Development in 2019 defines a skyscraper as a building with a fixed height of more than 100m.

and addresses, we geo-code each skyscraper's latitude and longitude. We also consolidate skyscrapers that consist of multiple towers.[6] The resulting sample consists of 545 skyscrapers: 447 commercial and the rest residential. Together these account for a substantial proportion (40.1%) of all skyscrapers (1359) in China.

Land Transaction Records We compile land transaction data from the official website of the Land Transaction Monitoring System (www.landchina.com), which is maintained by the Ministry of Natural Resource's Real Estate Registration Center. These data cover almost all land transactions (over 1.8 million) in China's primary land market between 2003 and 2017. Each transaction includes detailed information such as the location, price, parcel size, transaction method,[7] land use type (residential, commercial, industrial, public, or mixed use), floor area ratio (FAR) limitation, land evaluation grade, buyer, and seller. We convert each parcel's address into geo-referenced latitude and longitude coordinates using China's leading search engine, Baidu Map API,[8] which allows us to integrate each land transaction into a geographical information system (GIS) environment. We merge land parcels with a battery of locational characteristics including the distance to the CBD[9] and the distance to various public amenities. Specifically, using the 2006 nighttime light data without sensor saturation,[10] we identify the CBD by finding the brightest 1km×1km grid cell in each city's urbanized area (Baum-Snow et al., 2017; Tan et al., 2020). We also consider the possibility of polycentric urban structure, and define cells whose pixel value exceeds 80% of the brightest

[6]The raw data include 724 high-rise buildings, but some skyscrapers involve multi-tower development.

[7]Transactions can be carried out in four ways: two-stage auction (*guapai*); invited auction (*zhaobiao*); English auction (*paimai*); or bilateral agreement (*xieyi*).

[8]Source: https://api.map.baidu.com/lbsapi/.

[9]Three measures of distance to the CBD are used: the Euclidean distance to the CBD for a baseline; for robustness, the Euclidean distance to the nearest center (CBD and sub-centers) and the actual travel distance to the CBD over the road network, which is calculated using Open Source Routing Machine (OSRM) and 2020 OpenStreetMap (OSM) data (Huber and Rust, 2016).

[10]Source: the Global Radiance Calibrated Nighttime Lights published by the National Oceanic and Atmospheric Administration National Geophysical Data Center.

cell's as sub-centers. The geo-coded locations of public amenities (including public parks and railway stations) in 2010 are obtained from the China Geographical Information Monitoring Cloud Platform, which is maintained by the National Geomatics Center.

Land for Skyscraper Construction In a two-step process, we match each commercial skyscraper to the land parcel on which it was built. First, we employ the geo-coded information to select land parcels that meet four criteria: they must be designated for commercial or mixed-use, within 5 km of the skyscraper location, with a floor area ratio (FAR) limitation tied to the height of the corresponding skyscraper, and the transaction must have taken place at least 2 years prior to the skyscraper completion.[11] We then manually check these matches by comparing the recorded land buyer with the skyscraper's developer. The resulting match rate is 74.5%: 333 out of 447 commercial skyscrapers are successfully matched to the land parcels on which they were built. Among these matches, 247 skyscraper projects involved a single land parcel, while the other 86 projects used multiple land parcels. In total, 488 land parcels are precisely identified.[12]

Firm Registration, Business Amenities, and Infrastructure To gauge the economic activity surrounding skyscrapers, we obtain data on annual firm registrations (2003–2018) and local business amenities (2010–2017), totaling 15.9 million and 19.6 million observations, respectively. The firm registration data are sourced from the State Administration for Industry and Commerce, and the information on business amenities is extracted from the Gaode Map API (https://lbs.amap.com/). By geo-coding their locations, we then create a balanced panel of 1km $\times$ 1km grid-cells featuring the number of newly established firms and

[11]The minimum duration of skyscraper construction in China is 2 years (source:https://www.skyscrapercenter.com/country/china/buildings.).

[12]The Ministry of Land and Resources mandated the reporting of land transaction information only from 2007 onwards. Therefore, we may not be able to find a match in the land transaction records for land transactions occurred before for skyscrapers in the early years of our sample or those that had a longer-than-usual construction period.

local business amenities near skyscrapers.[13]

To assess infrastructure development in the vicinity of skyscrapers, we use the land transaction data to compile records of land parcels transferred for public infrastructure projects between 2003 and 2017 (106,295 transactions). Here we consider several types of parcels: those designated for the development of public transit facilities (including roads, railways, bus terminals, metro and train stations, ports, airports, and public parking spaces), schools, cultural and sports facilities, and hospitals. Because land designated for public use may extend well beyond the boundaries of the 1km×1km grid–cells, we calculate the number of those parcels at a larger spatial scale, specifically 1km rings surrounding each skyscraper.

3 What Drives the Skyscraper Boom in China?

China's rapid urbanization since 2000 has been accompanied by unprecedented growth in the number of tall buildings. Figure 1 illustrates that commercial skyscraper construction has been shifting from North America to China since the mid-1980s. In 2018 alone, a record 143 buildings over 200m tall were completed worldwide; 62% of these (88 high-rises) were in China. Five of the world's 10 tallest buildings, and 44 of the 100 tallest, are in China. This boom undoubtedly reflects the rapid economic growth and urban expansion that occurred in China over the past several decades, but it is also overshadowed by concerns about low occupancy and economic inefficiency.[14]

[13] Business amenities encompass a wide range of establishments, including restaurants of various types (snack bars, Chinese restaurants, Western restaurants, and cafes), banks, educational institutions, hotels of different categories (hostels and starred hotels), and retail facilities such as convenience stores, grocery stores, supermarkets, drugstores, shopping malls, and bookstores.

[14] See https://asiatimes.com/2019/05/china-now-a-kingdom-of-tall-empty-towers/.

3.1 Where are Skyscrapers Built?

Cross-city Distribution Figure 2 illustrates the geographic distribution of the 447 commercial skyscrapers over the sample period: 307 are located in coastal areas, 43 are in the central area and 97 are in the western area. We divide the cities in which the skyscrapers were built into four tiers based on population, GDP, and administrative hierarchy (Zheng and Kahn, 2013; Glaeser et al., 2017).[15] We show that 30.8% of the skyscrapers are located in tier–1 cities, 59.2% are in tier–2 cities, and 10% are in lower–tier cities. In stark contrast to the impression left by bustling construction, a survey reveals high office vacancy rates even in tier–1 and tier–2 cities, averaging 21.5% in the third quarter of 2019 (Shepherd et al., 2020).

Next, Figure 3 plots the average heights of the tallest skyscrapers against city GDP rank across all Chinese cities. The x-axis is ordered from left to right from the top-ranked to the bottom-ranked city in GDP. While it is not surprising that larger and more developed cities enjoy higher skylines, the construction of skyscrapers even extends to cities at the bottom of the GDP distribution. For example, Chongzuo and Baise are ranked 258 and 271 out of 285 cities in GDP, respectively, yet both added skyscrapers during our study period. Figure 3 highlights cities that issued preferential policies for skyscraper development in red. As shown, even in bottom-ranked cities, local government support is directed to skyscraper projects. Notably, seven of the ten cities with the lowest GDPs have published official documents encouraging skyscraper growth. Given the pattern illustrated in the figures, it is natural to ask: are all of the commercial high-rises and the associated government support they received economically justified, even those built in lower-tier and underdeveloped cities?

[15] Tier-1 cities include Beijing, Shanghai, Guangzhou, and Shenzhen. Some provincial capitals like Nanjing and top-performing prefecture-level cities like Suzhou are grouped into the second tier. Other smaller or underdeveloped cities fall into tiers 3 and 4.

Within-city Distribution We next turn to within-city patterns of skyscraper construction by contrasting the commercial and residential samples. According to neoclassical theory, the fundamental driver of skyscraper development is land–capital substitution in building service production: height is substituted for expensive land (Epple et al., 2010). The key implication is that skyscrapers should be sited and built taller near CBDs, where land prices are higher.

Motivated by this reasoning, we produce a stylized depiction of the location and height profile of skyscrapers in China. To do so, we generate a set of 1km-wide grids defined in terms of the distance to the CBD, and then assign the height of the tallest skyscrapers to their siting grids. As shown in Figure 4, the majority of skyscrapers are located within 10km of a CBD. Commercial skyscrapers near CBDs (Panel a) are taller than residential high-rises (Panel b), and the height of commercial skyscrapers drops faster than the height of residential skyscrapers as their distance to a CBD increases. This pattern could be explained by a relatively steep decay in the production amenity, a low input share of floor space in production, or a relatively low net cost of height in commercial development in a canonical model of urban horizontal and vertical development (Ahlfeldt and Barr, 2022). However, it is worth emphasizing that many more commercial skyscrapers are located farther from CBDs than their residential counterparts, and this feature can not be easily accounted for by the aforementioned forces.

We document a similar pattern in Table A1, where we report the coefficients from regressing the height and number of skyscrapers on distance to a CBD. At the intensive margin, the height of commercial skyscrapers falls more quickly than that of residential structures as one moves away from the CBDs. The pattern, however, reverses at the extensive margin: the number of residential skyscrapers in each 1km$\times$1km grid-cell (zero if there were none) decreases faster than that of commercial skyscrapers with distance from CBDs. Overall, there is excess construction of commercial skyscrapers farther away from CBDs. One explanation for this phenomenon is a high degree of polycentricity; urban subcenters emerge as new employment centers when land costs are high. Another intriguing explanation for the observed pattern is government actions intended to promote new urban subcenters in the suburbs.

To shed some light on the two possible explanations above, we quantitatively estimate how commercial and residential skyscraper development has responded to land costs, following a reduced-form empirical specification in the spirit of Ahlfeldt and McMillen (2018). The details of the estimation are reported in Appendix A2. In our preferred specification, we find that the price–quantity elasticity for commercial skyscrapers (0.081) is much smaller than that of tall residential buildings (0.132). This suggests that the neoclassical land–capital substitution likely plays a less important role in the location choice of commercial skyscrapers than that of residential high-rises. However, the recent skyscraper boom in China, especially projects placed farther away from CBDs and in smaller cities, actually appears to be driven more by explicit government interventions than market forces, an explanation that is also consistent with anecdotal evidence described in the following section.

3.2 Anecdotal Evidence of Commercial Skyscraper Subsidies

Local governments have heavily influenced China's remarkable boom in vertical structures. To explore the underlying incentives and policy measures, we compiled official documents issued by several Chinese cities that promote super high-rise projects. We also augmented these with supplemental information from news articles.

The documents and articles we analyzed for this study emphasize three primary motivations behind the avid support for skyscraper development in China. First, cities seek to demonstrate their urbanization achievements and improve their urban image by building high-rises.[16] Municipal governments highly value the "landmark" effects that skyscrapers generate, which they anticipate will attract visitors and residents—especially skilled workers and "high-end" industries—to their cities. Small cities utilize skyscrapers to set them apart

[16]Source: https://www.scmp.com/property/hong-kong-china/article/2070761.

from their competitors in the region, while larger cities are more likely to build them on the urban periphery to boost new town development. Second, commercial skyscraper construction is perceived as a powerful engine for local economic growth, and is thus inevitably intertwined with local government officials' career concerns (Xu, 2011). Barr and Luo (2021) document a positive relationship between officials' promotion incentives and skyscraper construction. Finally, since the fiscal decentralization reform in the mid-1990s, local governments have sought extra-budgetary revenue—especially land revenue—to finance local expenditures (Han and Kung, 2015). Local governments, therefore, tend to place skyscraper projects in new towns that have an ample supply of undeveloped land. They then strategically develop parcels near the skyscrapers for commercial or residential use with the expectation of selling them at a premium. In summary, these institutional features—regional competition for urbanization, a career promotion system tied to economic success, and pressure to raise land revenue—shape Chinese commercial skyscraper construction beyond the conventional market forces of supply and demand.

Turning to the support measures, Table A4 shows a list of preferential policies implemented by 28 cities (ranked by their GDP in 2010). As shown in Columns 3–4, local governments tend to intervene in the commercial skyscraper market using a toolkit of policies including land discounts, tax reductions, and cheap credit. Land price discounts are particularly common. They make up the majority of government subsidies because city leaders have significant control over urban land supply and development (Lichtenberg and Ding, 2009; Wang et al., 2020).[17] Furthermore, Columns 2, 5 and 6 show that local governments are more likely to subsidize skyscraper projects that have a commercial function, and to do so in underdeveloped cities and new towns (i.e., suburban areas). In the following section, we provide empirical evidence as to *when* and *how* local governments grant land discounts to skyscraper projects over the public land transactions.

[17] In China, the state owns the land, and sub-national governments are the sole sellers in the local primary land market. Local governments in China convey land to market entities by commoditizing and leasing land use rights in long-term contracts (40, 50 or 70 years).

3.3 Discounted Land Prices for Commercial Skyscraper Construction

In this section, we seek to accurately quantify the empirical magnitude of the land discounts granted to commercial skyscraper developers. To do so, we generate a spatially matched sample of transactions involving land parcels for commercial skyscraper construction (commercial skyscraper land, hereafter) and other surrounding commercial land parcels (non-skyscraper land, hereafter) that were sold before the skyscraper was built (see Figure A2). The geo-matching radius was initially set to 10km and later restricted to 5km and 2.5km. For the sake of statistical power, we remove matched pairs with less than three observations. Conditional on observed land characteristics and access to public amenities, these parcels are assumed to be highly comparable in quality and underlying market value. We then attribute any transaction price difference between commercial skyscraper land and adjacent non-skyscraper land to local governments' preferential treatment of skyscraper projects.

Empirical Specification We follow the spatial matching approach of Chen and Kung (2019) and estimate the land price discount using the following regression:

$$\ln(P_{ijt}) = \beta_1^D CommercialSkyscraperLand_{ijt} + \gamma^D X_i + \theta_j^D + \alpha_t^D + \varepsilon_{ijt}^D \tag{1}$$

where the dependent variable P_{ijt} is the land transaction price of parcel i within a 10km (5km, 2.5km) radius of skyscraper j sold in year t. The key explanatory variable of interest, denoted by $CommercialSkyscraperLand_{ijt}$, is a dummy variable equal to 1 if parcel i was sold in year t to construct commercial skyscraper j, and 0 otherwise. The coefficient of interest is β_1^D. It indicates the difference in the price of skyscraper vs. non-skyscraper land within a small geographic area. In all specifications, we control for a rich set of parcel-level covariates, including the logarithm of the size of the land sold and its square, the transaction method (English auction, two-stage auction, bilateral agreement, or invited auction), the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, and access to public amenities (the logarithm of the distance to the nearest public park and rail station). We also include the spatial trend (the latitude and longitude differences between the parcel and the skyscraper $\times$ the year trend) as a control to capture potential unobservable factors correlated with distance (Ahlfeldt et al., 2023). Furthermore, to limit the comparison within land parcels located close to the same skyscraper and sold in the same year, we control for skyscraper-matched pair fixed effects θ_j^D and year fixed effects α_t^D. Robust standard errors are clustered at the matched pair level. ε_{ijt}^D is an error term.

Results Panel A of Table 2 presents the results of the estimation using Equation (1). Column 1 uses a matched sample within a broader 10km radius of the skyscrapers. The coefficient on the main indicator variable $CommercialSkyscraperLand_{ijt}$ represents a discount rate of 31.4% ($e^{-0.377} - 1$) and is statistically significant at the 1% level. In columns 2 and 3, we further restrict our analysis to 5km and 2.5km radii, where parcels are even more similar in terms of land attributes. The magnitude of the estimated coefficient for $CommercialSkyscraperLand_{ijt}$ increases. In our preferred specification (column 3), the land price discount received by commercial skyscraper developers is 40.1% ($e^{-0.512} - 1$).[18] In a placebo analysis, columns 4 through 6 repeat the regression using a matched transaction sample of land parcels designated for residential skyscrapers and nearby residential land plots. The positive and insignificant coefficients for the main indicator indicate the absence of land price discounts for residential skyscrapers.[19] Taken together, these findings provide compelling evidence that in China, there are land price discounts exclusively offered for commercial skyscraper developments. This finding is consistent with the earlier results showing low height–land value elasticity, and with government documents that explicitly encourage

[18]Table A5 reports the results of robustness checks. Columns 1–2 restrict the geo-matching radius to 2km or 1km. Columns 3–4 specify the number of observations in each matched pair to be no fewer than 10 or 15. Reassuringly, the estimates range from -0.496 to -0.617, similar to our baseline estimates.

[19]A plausible explanation for the positive coefficient is that certain land use regulations on FAR are relaxed on these residential parcels, and are thus reflected in the transaction prices (Brueckner et al., 2017).

commercial skyscraper development.

In practice, how have land discounts been granted to developers? Cai et al. (2013) has documented that local officials can strike pre-auction side deals with favored bidders through two-stage auctions. Specifically, the local land bureau announces the auction including the parcel characteristics, the reserve price, and any special requirements, and invites bidders to enter the auction. If more than one bidder enters, an English auction takes place in the second stage. The first stage can help favored developers signal that the parcels are taken, thus deterring the entry of other competitors. The favored bidder can then obtain the land at a price that is very close to or equal to the reserve price. To validate this channel, we leverage documents on the bidding procedures released by the local land bureaus in some skyscraper cities and data on reserve prices from a subset of land transactions. We find three key pieces of evidence that local governments indeed deploy such a strategy to grant developers implicit land price discounts. First, a majority (60%) of land parcels used for commercial skyscrapers are sold via two-stage auctions. Second, there is typically a high threshold for entry into an auction, which deters non-preferred bidders (Zhu, 2012). A review of bidding details suggests that the qualification requirements for developers to enter two-stage auctions of skyscraper land are quite restrictive.[20] Finally, the reserve prices for commercial skyscraper land parcels are set much lower than those for nearby non-skyscraper land parcels. This effectively sets lower anchors for the transaction prices for skyscraper land since 90% of the parcels were sold at the reserve price or with only a slight premium (see details in Figure A3).

Panel B of Table 2 reports regression results of Equation (1) by using the logarithm of reserve prices in land auctions as the dependent variable. The coefficients on the indicator variable $CommercialSkyscraperLand_{ijt}$ in columns 1–3 represent the estimated discount rate in reserve prices, ranging from 36% ($e^{-0.447}-1$) to 47.6% ($e^{-0.647}-1$). They could also

[20]For example, a two-stage auction of a land parcel in Zhongshan City specified FAR$<$7 (intended for a commercial skyscraper) and required the developer to be ranked in the top 200 of the Fortune 500 list (2017–2019), to hold a financial permit issued by the China Banking and Insurance Regulatory Commission, and to have registered capital over 20 billion RMB (3 billion USD). See https://zs.fang.ke.com/loupan/zhuanti/58143.html for more details.

be viewed as the upper bound estimate of land discounts granted to commercial skyscraper projects, and so are larger than the baseline estimates (31.4%–40.1% in Panel A). Columns 4–6 again repeat the analysis for residential skyscrapers, and the estimates are close to zero, showing no signs of reserve price manipulation for land parcels intended for residential skyscrapers.

Heterogeneity in Price Discounts for Commercial Skyscraper Land Since local governments monopolize the land supply in China, we further examine local officials' political incentives to provide subsidies that encourage skyscraper construction in their cities. The results are presented in Table 3. The career advancement of Chinese municipal officials is closely tied to their cities' economic performance (Qian and Xu, 1993; Li and Zhou, 2005). In related research, the promotion chances of city leaders with short tenure expectations improved when they initiated long-term investment projects such as subways, even though they were unlikely to remain in office through the completion of the project (Lei and Zhou, 2022). We hypothesize that ambitious city leaders, especially mayors,[21] have stronger incentives to support skyscraper construction that induces urban growth, with the ultimate aim of getting promoted.

Column 1 formally tests this proposition by interacting the commercial skyscraper land dummy with respective career incentive indicators for the municipal mayor and the party secretary.[22] This indicator switches to 1 if the career-incentive intensity estimated in Table

[21]It has been well-documented in the political economy literature that despite party secretaries being the *de facto* highest-ranking officials in cities, they mainly manage party affairs, while the mayor is the executive officer of the municipal government, with responsibility for administrative affairs, including land development planning, capital investment, and other resource allocation decisions (Xu, 2011).

[22]To measure the career incentives for the mayor and the secretary, we use city leader data (detailed in Section A1) and follow the estimation approach proposed by Wang et al. (2020): we regress the promotion dummy (which equals 1 if the city leader was promoted to a higher-level position by the end of their term) on various characteristics of the leader (age, political hierarchy level when they entered office, and educational attainment). The estimated coefficients, which are independent of the leaders' *ex post* performance, are used to predict the *ex ante* promotion likelihood of each city leader in the sample. The prediction is used as a proxy for their career incentive intensity, as a city leader with higher chances of promotion may be more motivated to stimulate local development to advance their career. Table A6 reports the results using a linear probability model and a probit regression.

A6 is above the sample mean. We matched each commercial skyscraper project in our sample with information about the mayor and party secretary who were in office when the project began. The estimated coefficient of the mayor interaction term is significant and negative, while it is imprecisely estimated for the secretary interaction term. These results confirm that mayors who were more likely to be promoted provided greater land price discounts to commercial skyscraper projects in their jurisdictions, while party secretaries had very little influence on land allocation.

We next explore the response of skyscraper land price discounts to a nationwide expansion in investment—the 2009 economic stimulus plan.[23] This plan greatly enhanced local governments' fiscal capacity to support commercial skyscraper development. Since approximately 90% of local government investments were financed through bank loans in 2009 (Bai et al., 2016), we collect data on new loans granted by commercial banks between 2007 and 2012. We then calculate the post-2009 bank loan growth rates at the city level, which we use to measure the size of each city's stimulus package. Column 2 interacts the commercial skyscraper land dummy with the stimulus package indicator. This indicator equals 1 if the land transaction took place after 2009 and in a city where commercial lending grew faster than the national average between 2007 and 2012. The negative coefficient indicates that the economic stimulus plan magnified the land subsidies granted to commercial skyscraper projects.

We recognize that there are plausible alternative explanations for these findings. For example, our estimates of land price discounts could be interpreted as representing corruption in the primary land market or collusion between local governments and developers rather than support for commercial skyscraper projects. To test the first alternative interpretation, we construct two measures of corruption. First, we calculate the total number of city-level

[23]In the wake of the 2007 global financial crisis, Chinese premier Wen Jiabao initiated a 4 trillion RMB stimulus package; its main component provided support for infrastructure and construction projects (Chen et al., 2020).

corruption cases involving local land bureau officials between 2010 and 2016.[24] Second, we create a measure related to the anti-corruption campaign that began with the official release of the Eight-Point Stipulations in 2012 (Chen and Kung, 2019). The indicator, which captures potential measures put in place to limit corruption, equals 1 if a land transaction took place after 2012, and 0 otherwise. Column 3 introduces an interaction term between the commercial skyscraper land dummy and a measure of city j's total number of land corruption cases (cumulative). The coefficient on the interaction term is negative and statistically insignificant. Importantly, the estimates of the main effect remain stable. Column 4 interacts the commercial skyscraper land dummy with an indicator for the anti-corruption campaign. The coefficient on the interaction term is positive and of a small magnitude. Although it is imprecisely estimated, the anti-corruption campaign appears to slightly lower the discount rate. The main effect is still strongly significant and highly robust.

To assess the possibility of government–firm collusion, we examine whether commercial skyscraper developers of varying backgrounds received different levels of subsidies. We categorize the developers into three groups according to their ownership: state-owned enterprises (SOEs), privately-owned enterprises (POEs), and foreign-owned enterprises (FOEs). Intuitively, given the political landscape in China, government officials might be more prone to colluding with SOE developers. As shown in column 5, there are no significant differences in the land subsidies granted to developers with different types of ownership. Further, we explore the extent of local ties by distinguishing between local and non-local developers. The underlying assumption is that the former would be more likely to collude with the local government (Fang et al., 2022). Column 6 reports a negative but insignificant coefficient on the interaction term, providing some suggestive evidence that local governments may favor local developers by offering them greater land discounts. The main effect remains robust and similar in magnitude to the baseline. Overall, we establish that land discounts offered

[24] The data is sourced from China Judgments Online (https://wenshu.court.gov.cn/), maintained by the Supreme People's Court of China. We manually collected court verdicts related to land corruption, representing a total of 584 cases.

to commercial skyscrapers are primarily manifestations of preferential policy support, more than alternative interpretations such as land market corruption and government-developer collusion..[25]

4 Economic Returns of Commercial Skyscrapers

Empirical Specification As previously described in Section 3, local governments promote commercial skyscraper development in the hopes of attracting skilled labor and high-value-added firms, and creating productive local agglomerations. The purpose of this section is to empirically evaluate whether this rationale for offering commercial skyscraper subsidies is validated by evidence. Specifically, we examine whether the arrival of commercial skyscrapers increases the land value of surrounding parcels. Our strategy assumes that any external benefits (or costs) of commercial skyscrapers to nearby areas are reflected in the value of adjacent land (Ahlfeldt and Kavetsos, 2014; Pope and Pope, 2015).

We generate a spatially matched sample of commercial land parcels located near a commercial skyscraper, excluding the skyscraper's land. When choosing the size of the treatment and control areas, it is hard to precisely project the spatial scale of the external impacts of commercial skyscrapers *ex ante*. Notably, the closer the control group is to the treatment group, the more comparable it is to the treatment group in unobserved local factors, and at the same time, the more likely it is to be exposed to spillover (or siphon) effects, which could lead to the underestimation (or overestimation) of the treatment effect. We begin by experimenting with land parcels located 7–8km away from a commercial skyscraper as the control group, and investigate the skyscraper spillovers on the value of land parcels located

[25] Our evidence is not sufficient to rule out the corruption channel either since not all corruption cases have been discovered and documented.

within 7km of a commercial skyscraper. We run regressions of the form:

$$\ln(P_{ijrt}) = \alpha^P_{jt} + \theta^P_{jr} + \sum_{r=1}^{7} \beta^P_r D^r_{ij} * \text{Post}_{ijt} + \gamma^P \boldsymbol{X}_i + \varepsilon^P_{ijrt} \tag{2}$$

where P_{ijrt} is the land value of parcel i in ring r around a commercial skyscraper j at year t. By using P_{ijrt} as our key outcome variable, α_{jt} is a skyscraper-matched-sample j-year t fixed effect, which captures shocks common to all parcels near the same commercial skyscraper in year t. D^r_{ij} are indicator variables for individual parcel i within the $r-1$ to r km radius around a commercial skyscraper j, while the $7-8$km ring is the reference group. θ_{jr} is a skyscraper j–ring r fixed effect, which captures pre-existing differences in the land prices between the treatment and control groups of parcels. Post_{ijt} is an indicator variable for whether parcel i's transaction in year t took place after the completion of the corresponding commercial skyscraper j. $\boldsymbol{X}_i$ are the observable characteristics of individual parcel i as previously defined. We also include the spatial trend (the latitude and longitude differences between the parcel and the skyscraper $\times$ the year trend) as a control to capture potential within-ring unobservable factors. ε^P_{ijrt} is the error term. The standard errors are clustered at the skyscraper–matched sample level.

Panel (a) of Figure 5 plots the coefficients of primary interest β^P_r, which capture any distance-dependent spillovers generated by commercial skyscrapers. On average, the value of land parcels between 0 and 1km from a skyscraper increases by about 50% ($e^{0.406}-1$) after skyscraper completion, relative to the omitted category of land parcels sited between 7 and 8km from a skyscraper. The spillover effects decrease rapidly with distance from the commercial skyscraper, leveling off at around 2km. In another exercise, we define the distance buffers in a more flexible way. Instead of using 1km rings, we divide the sample of land parcels within 8km of commercial skyscrapers into a set of 20 quantile-spaced intervals, following Butts (2023). Parcels in the $19-20^{th}$ quantile in distance to the skyscraper serve as the reference group. We then repeat Equation (2) with this alternative definition of nonparametric buffers. Panel (b) of Figure 5 displays the results. Overall, the two methods yield very similar patterns: only land parcels located within 2km of a commercial skyscraper are positively affected.

With this in mind, in our baseline specification, we then restrict our sample to land parcels located within 3km of a commercial skyscraper. We define the treatment areas as the 2km–radius circles around each commercial skyscraper, and the control areas as the 1km–radius rings circumscribing each treatment area. To allow for a meaningful causal evaluation, we exclude those commercial skyscrapers that were matched with fewer than three observations of land parcels transactions in either the period before or after the treatment (the completion of the skyscraper). This leaves us with 293 commercial skyscrapers and 3,301 matched land parcels. Figure A4 illustrates our choice of treatment and control groups. In essence, our empirical specification is a spatial difference-in-differences (DID) analysis that compares the changes in land value before and after a commercial skyscraper was built between land parcels within 0–2km of the skyscraper (treated) and those within 2–3km (control). This particular choice carefully balances the comparability of the treatment and control groups and concerns that the control group might be contaminated. We re-write Equation (2) as:

$$\ln\left(P_{ijrt}\right) = \alpha_{jt}^{P} + \theta_{jr}^{P} + \sum_{r=1}^{2} \beta_{r}^{P} D_{ij}^{r} * \mathrm{Post}_{ijt} + \gamma^{P} \boldsymbol{X}_{i} + \varepsilon_{ijrt}^{P} \tag{3}$$

where D_{ij}^{1}, D_{ij}^{2} are indicator variables for individual parcel i within the $0-1$ or $1-2$km ring around a commercial skyscraper j. The $2-3$km ring serves as the reference group. All other variables are as defined previously, and the standard errors are clustered at the skyscraper–matched sample level. Our key parameters of interest are β_{1}^{P} and β_{2}^{P}, which identify the local spillover effects of commercial skyscrapers on the spatial rings surrounding them.

Results Table 4 presents the results. In column 1, the estimated coefficient on the interaction term "0–1km * Post" is 0.493 and statistically significant, suggesting that land parcels for commercial use located within 1km of a commercial skyscraper sold for approximately 63.7% ($e^{0.493} - 1$) more than the control group (those within $2 - 3$km) after the construction of the skyscraper was complete. Meanwhile, the coefficient on "1–2km * Post" is much smaller in magnitude and only marginally significant. The results imply that commercial skyscrapers generate sizable positive spillovers, which are reflected in the value of nearby land. Yet this premium effect is very local and decays dramatically with distance from the focal skyscraper. Column 2 adds spatial year trends (the latitude and longitude differences between the parcel and the skyscraper interacted with the year trend) as an additional control variable. This flexibly allows the underlying trend in the land prices of nearby plots to differ from that of the skyscraper plot, varying smoothly in distance. Column 3 repeats the spatial DID analysis but conducts a "donut" analysis with land parcels located 3–4km away from a commercial skyscraper as the control group. The estimates of skyscraper spillover effects remain stable in the alternative specifications.

Although estimates of the average spillovers of *all* commercial skyscrapers are useful, the question that has particular policy relevance is whether such spillovers exist for *subsidized* skyscrapers. In other words, does the urban investment supported by heavy government subsidies (i.e., land price discounts) pay off? To shed light on this question, column 4 interacts the treatment indicators with a measure of land subsidy $SubsidyRate_j$, which denotes the land price discount rate granted to commercial skyscraper projects,[26] showing that a higher subsidy rate leads to lower spillover effects. Column 5 interacts the treatment indicators with a subsidy dummy $Subsidy_j$, which switches to 1 if the commercial skyscraper received any positive land subsidy. To deal with the bias stemming from measurement error in the estimated subsidy rates (especially those rates close to zero), column 6 employs an alternative subsidy dummy, which equals 1 if the commercial skyscraper received a land

[26]To calculate the skyscraper-level land subsidy rate, we run the regression of the unit land price on a host of parcel characteristics, using the sample as in column 3 of Table 2. The residuals are then used to compute the price difference between non-skyscraper land and commercial skyscraper land, allowing us to infer the subsidy rate for each commercial skyscraper project. This process leaves us with subsidy information on 148 commercial skyscrapers and 2,015 commercial land parcels.

subsidy rate significantly higher than zero.[27] All the interaction terms between $D^1_{ij} * \text{Post}$ and different subsidy measures are large, negative, and statistically significant. A joint significance test for the coefficient of $D^1_{ij} * \text{Post} * Subsidy_j$ in tandem with that of $D^1_{ij} * \text{Post}$ indicates that subsidized skyscrapers generate much smaller and statistically insignificant spillovers than skyscrapers in general.

Robustness We conduct three additional analyses to further verify the validity of the identification strategy. First, we use an event study approach to check the parallel-trend assumption, regressing land value on the interaction terms of the leads and lags of the commercial skyscraper entry year dummy and ring indicators with the same controls as in Equation (3). In order to improve the statistical power, parcels sold 6 or more years after a skyscraper's completion are categorized in the event window "6 (plus)," and those sold 4 or more years prior to completion are categorized in the event window "-4 (minus)." The event study specification takes the form:

$$\ln\left(P_{ijrt}\right) = \alpha^P_{jt} + \theta^P_{jr} + \sum_{n=-4, n\neq -1}^{6} \sum_{r=1}^{2} \beta^P_{rn} D^r_{ij} * \text{Period}_{ijt+n} + \gamma^P \boldsymbol{X}_i + \varepsilon^P_{ijrt} \tag{4}$$

where Period_{ijt+n} is a dummy variable, indicating the time relative to the skyscraper completion event, which is equal to 1 if the land transaction took place n years before $(n < 0)$ or after $(n \geq 0)$ the skyscraper's completion. The omitted category $(n = -1)$ is the year prior to the skyscraper's completion. β^P_{rn} are the key coefficients of interest, which estimate the land value outcome of ring r at a given year n relative to the omitted category. Panel A of Figure 6 presents the results. As shown, there is no clear pre-trend in the land value near a commercial skyscraper during the years leading up to the skyscraper's construction

[27] To do so, we perform a one-sample T-test for each commercial skyscraper, calculating the mean price difference between commercial skyscraper land and non-skyscraper land and the standard error of this difference. We define $\mathbf{1}\{Subsidy > 0(significant)\} = 1$ if the difference is significantly above zero at a 95% confidence level.

and completion.[28] Land prices start to appreciate only after the construction is complete. However, the positive effects do not persist for long, as indicated by the coefficients of event years "5" and "6." Panel B further distinguishes between subsidized and unsubsidized commercial skyscrapers. A skyscraper is defined as "subsidized" if its land transaction price is *significantly* smaller than the matched surrounding land parcels. Subsidized commercial skyscrapers provide little land value premium during the study period. By contrast, unsubsidized ones generate larger spillover effects on nearby land values, and the positive effects tend to persist over time.

Second, one might worry that the local supply of land, dominated by local governments, might respond to commercial skyscraper development with a concerted effort to boost local agglomeration. Thus, we further explore whether there was a significant change in the quantity or quality (in terms of distance to the CBD, transaction method, parcel size, and land evaluation grade) of land transactions after a skyscraper was completed. Table A7 reports the estimation results, which indicate that the completion of commercial skyscrapers has no impact on either the quantity or quality of the newly supplied land parcels nearby. Our analysis can thus rule out the supply-side explanation.

Third, we employ a spatial randomization inference test to demonstrate that the baseline results are not spurious due to a mis-specified empirical model. We construct counterfactual locations selected at random from within 5km of a commercial skyscraper, while keeping the year of their completion unchanged. We re-estimate the main coefficient of interest (the coefficient on the interaction term "0–1km * Post") using the baseline specification. To increase the statistical power of the randomization test, we repeated this procedure 2,000 times. Figure A5 illustrates the density distribution of the point estimates from the 2,000 runs. The red line, which presents the benchmark estimate of 0.696, lies outside the 99% confidence interval of those placebo estimates. The results suggest that spillovers occurred

[28] In general, commercial skyscrapers are completed less than 4 years after their construction is announced, as shown in Table 1.

only in the observed skyscraper areas, not in the neighborhoods of the counterfactual sites. The p-value (0.01) allows us to reject the possibility that a mis-specified empirical model drives the results related to commercial skyscrapers' spillovers.

Alternative Outcomes We have thus far presented evidence of commercial skyscrapers' spillover effects—which are quite local—on the land value of surrounding areas. Although the regressions included a rich set of observable parcel characteristics, it is unclear to what extent the transaction price of land reflects its true market value in China, given the state-owned land use rights. To address this issue, we directly examine the impact of skyscraper arrival on economic activity nearby. We create a balanced panel of 1km $\times$ 1km grid-cells reflecting the number of newly established firms (2003–2018) and local business amenities (2010–2017), and then estimate the following regression:

$$\ln\left(Y_{ijt}\right) = \alpha^{Y}_{jt} + \lambda^{Y}_{i} + \sum_{r=1}^{2} \beta^{Y}_{r} D^{r}_{ij} * \text{Post}_{ijt} + \varepsilon^{Y}_{ijt} \tag{5}$$

where Y_{ijt} is the outcome of interest, which captures economic activity in grid-cell i in year t near commercial skyscraper j. α_{jt} is a skyscraper-matched-sample j-year t fixed effect, and λ_i is a grid-cell i fixed effect. D^1_{ij}, D^2_{ij} are indicator variables for grid-cell i located $0-1$ or $1-2$km from skyscraper j. The $3-4$km ring serves as the control group. ε^{Y}_{ijt} is the error term. Robust standard errors are clustered at the grid–cell level.

Table 5 reports the estimation results. Column 1 indicates that a commercial skyscraper increases the number of newly-registered firms by 6.6% ($e^{0.064}-1$) within a 1km radius, while spillovers within the 1–2km buffer from the skyscraper decay considerably, and the estimates are no longer significant. Column 2 interacts the two treatment indicators with a measure of land subsidy $SubsidyRate_j$, and column 3 interacts the treatment indicators with a subsidy dummy $Subsidy_j$, where the subsidy terms are as previously defined. The estimates indicate that the spillovers of subsidized skyscrapers on firm registrations are smaller in magnitude and are not statistically significant. Figure 7 presents event-study results as to how commercial skyscraper completion has affected firm agglomeration over time. For subsidized commercial skyscrapers, the coefficients of all event time indicators (both pre- and post-completion) are not significant (plotted in gray circles). By contrast, although we find no differential pre-trends, the difference in firm registrations right next to and at a distance from the non-subsidized commercial skyscrapers begin to diverge quickly post-completion, and remain significantly positive in the longer period (plotted in black squares). Reassuringly, the dynamic pattern is similar to those observed for the land premium. Columns 4–6 use the log number of business amenities as the dependent variable. The results again confirm the absence of positive externalities from subsidized commercial skyscrapers. Taken together, these findings regarding economic activity lend further support to our baseline results, with fairly consistent magnitudes and spatial patterns.

5 Interpretation and Discussion

5.1 Potential Channels

Our principal finding is that subsidizing commercial skyscrapers' construction has *not* achieved local governments' intended objective of fostering new urban agglomerates. We now propose and evaluate evidence of plausible reasons for this lack of spillover effects.

First, the intensity of spatial spillovers is closely tied to the locations of commercial skyscrapers, which have primarily been determined by local governments. As presented in Columns 2–3 of Table A8, larger subsidies were granted to motivate developers to build in smaller cities and new towns located farther from CBDs. Naturally, these sites have lower urban density and lagging infrastructure, which could potentially impede the attraction of businesses.

In addition, the locational advantages or disadvantages of skyscraper sites could be magnified or offset by follow-up infrastructure investments, such as public transit and other amenities. The willingness of firms to locate themselves in or near those commercial skyscrapers crucially hinges on the accessibility of the sites, which affects workers' commuting costs. To test whether more complementary investments are made in the vicinity of subsidized skyscrapers, we compare the changes in the number of land parcels supplied by local governments for public infrastructure projects (including public transit, schools, cultural and sports facilities, and hospitals) near subsidized and unsubsidized commercial skyscrapers, using a variant of Equation (3):

$$\ln\left(N_{rjt}\right) = \alpha_{jt}^{N} + \theta_{jr}^{N} + \sum_{r=1}^{2} \beta_{r}^{N} D_{j}^{r} * \text{Post}_{rjt} + \sum_{r=1}^{2} \delta_{r}^{N} D_{j}^{r} * \text{Post}_{rjt} * \text{Subsidy}_{j} + \varepsilon_{rjt}^{N} \tag{6}$$

where N_{rjt} is the logarithm of the number of public land parcels supplied by the local government in ring r around commercial skyscraper j in year t. D_j^r are indicator variables that equal 1 if the ring is within a $r-1$–to–r km radius of commercial skyscraper j, while the $3-4$km ring serves as the reference group. All other variables are as previously defined. We estimate two parameters β_1^N and β_2^N, which capture infrastructure development in each of the two rings around non-subsidized skyscrapers.

Table 6 reports the regression results. Column 1 shows that a commercial skyscraper increased the number of newly supplied land parcels for public transit and amenity development within a 0–1km radius by 23.9% ($e^{0.215}-1$). Columns 2 and 3 interact the two distance band treatment indicators with the land subsidy rate or the subsidy dummy. The significant and negative coefficients of the interaction terms between subsidy measures and "0–1km * Post" indicate that subsidized skyscrapers receive fewer complementary investments from local governments. A likely explanation is that local governments lack fiscal resources due to the substantial land price discounts they provided to the developers of subsidized skyscrapers, given that land sales are an important source of revenue for them. Figure A6 presents the event-study results, visually displaying the time pattern of the impacts of skyscraper completion on the public land supply nearby. For subsidized commercial skyscrapers, the coefficients on all periods do not differ significantly from zero. In contrast, land parcels allocated for public projects surge immediately following the completion of unsubsidized commercial skyscrapers. The divergent trends in complementary investments magnify rather than mitigate the initial disparities in the locational choice between subsidized and unsubsidized skyscrapers.

Second, the lack of spillovers could be driven by the slow or unsatisfactory development process of skyscraper projects. There is considerable anecdotal evidence that some new state-initiated CBDs have failed to deliver for this reason. The Wuhan Wangjiadun CBD is one example. Its planning started in 2001, and subsequent construction commenced in 2006. However, the main developer of the project, Oceanwide, was overwhelmed by the multiple high-rise projects it had initiated worldwide, and experienced capital chain ruptures.[29] The Wangjiadun project thus slowed down and has still not generated any positive effects in terms of local development.

Subsidies could worsen the principal–agent problem between local governments and commercial real estate developers. On the one hand, discounted land prices magnify the adverse selection issue, and attract less experienced and less financially stable developers. On the other hand, there could be an *ex post* moral hazard problem: the winning bidder of a skyscraper project might not have a strong incentive to maximize efficiency after receiving subsidies. To assess these two channels, we collect comprehensive firm operation data for 228 skyscraper developers from the China National Tax Survey Database (2007–2016) and firm registration data (2003–2018), including the number of lawsuits in which they were involved, a dummy representing whether the developer was listed among dishonest debtors, and debt–to–asset (DTA), debt–to–equity (DTE), and cash–to–debt (CTB) ratios.[30] Columns 1–5 of Table 7 investigate the bivariate relationship between the subsidy received (measured by

[29] Source: https://www.bloomberg.com/news/articles/2021-10-29/chinese-developer.

[30] According to China's *Three Red Lines* policy, the supervision and regulatory authorities consider a DTA ratio>70%, a DTE ratio>100%, and a CTB ratio<100% as three alarming indicators of developers' financial conditions. If a developer breaches one or more of these "red lines," the central regulator will impose more financing constraints on the firm to reduce risk.

the subsidy rate) and the developer's quality (proxied by its past financial performance). Columns 1–2 indicate that subsidized developers were more likely to be involved in lawsuits and to be listed as dishonest debtors. Columns 3–4 show some tentative evidence that, on average, subsidized developers had a much higher leverage ratio before construction began. Column 5 suggests that, on average, subsidized developers had a much lower cash-to-debt ratio before construction began. Column 6 further shows that the construction duration of subsidized commercial skyscrapers tended to be significantly longer than their non-subsidized counterparts, a finding that could be driven by both adverse selection and moral hazard. In summary, these results suggest that subsidized commercial skyscrapers tend to be built by developers with worse credit history and more financial risk, and at a slower pace, providing evidence for both channels emphasized in the agency literature.

5.2 Linking Potential Channels to Commercial Skyscraper Spillovers

We then examine whether the aforementioned characteristics of subsidized skyscrapers can explain the lack of spillovers. Specifically, we augment the analysis in Section 4 by interacting the treatment indicator (0–1km * Post) with skyscraper characteristics including locational fundamentals and government-led complementary investments, and observe changes in the coefficients of "0–1 km * Post * $SubsidyRate_j$".[31]

Table 8 presents the results. Column 1 repeats the baseline estimate (column 4 of Table 4) for reference. Next, columns 2–4 include the interaction terms between "0–1km * Post" and various measures of location characteristics. The spillovers appear to increase when the skyscraper is located in top-tier cities or in a CBD. Column 5 further includes the interaction term with government-led complementary investments measured in terms of the cumulative number of public land parcels supplied by local governments within a 5km radius of the commercial skyscraper between 2003 and 2017. The estimate suggests that more complementary

[31] We omit the interaction terms with developer quality measures because only a subset of skyscrapers can be matched to developer information. It is difficult to make a meaningful comparison across specifications with large sample differences.

investments lead to substantially greater spillovers. Column 6 reports the results with the full set of local fundamentals and complementary investments in one regression, which again yields similar results.

To better quantify the mediation effects of these factors, we follow the two-step mediation procedure proposed by Acharya et al. (2016),[32] and compare the estimated de-mediated average controlled direct effect (ACDE) to the main effect. The gap between the main effect, captured by the coefficient on "0–1km * Post * $SubsidyRate_j$," and the corresponding ACDE illustrates the role of the mediators.

We report the ACDE/main effect ratio at the bottom of the table. In column 6, after partialling out the mediation effects of location characteristics and public facilities supply, the ACDE of "0–1km * Post * $SubsidyRate_j$" is no longer statistically significant, and the magnitude is 45% of the original treatment effect estimated in the main analysis. This suggests that more than half of the gap in spillovers between subsidized and unsubsidized skyscrapers is accounted for by the differences in location advantages and subsequent nearby government investments between these two groups of skyscrapers.

Admittedly, our empirical approach might not capture all external benefits of skyscrapers. Although we detect no increase in land value, business registrations, or public investments near subsidized skyscrapers 5 to 10 years after their completion, one might expect skyscrapers to promote the image of cities and bring benefits beyond the local effects. However, in Table A9, we look at the impacts of skyscraper projects on the average land value and the number of businesses at the city level and detect no significant effects. In addition, it is arguable that agglomeration clusters could take an even longer time to develop. However, our optimism about future benefits is limited for two reasons. First, the lack of follow-up public transit investments around subsidized skyscrapers limits their attractiveness. Second, given the

[32]The mediation procedure is performed in two steps. In the first step, we remove the effects of the mediator variables from the dependent variable. In the second step, we obtain the average controlled direct effect (ACDE) of the de-mediated dependent variable on the treatment variables. This method has been used in various recent economic studies (Moya, 2018; Brown et al., 2019; Gershenson et al., 2022).

persistence of China's low fertility rate, the country's decades-long urbanization push may have reached a bottleneck. Notably, the rural-to-urban migration rate rose by less than 1% in 2021 for the first time in 25 years[33].

Set against the potential long-term benefits, which may or may not materialize, there is a growing concern about the short-term financial burdens on developers and municipal finance. On one hand, many developers were already struggling to endure a debt crisis and were unable to finish their skyscraper projects without sustained government support.[34] On the other hand, as these projects fail to generate the expected positive spillover effects in the form of an increase in land revenue in the short run, they exacerbate the strain on local municipal finances and add to the growing concerns of an impending local-government debt crisis.[35]

6 Conclusion

Skyscrapers are an iconic symbol of China's rapid urbanization. Using rich geocoded data sets, this paper has presented empirical evidence about the underlying drivers and the efficiency of state-led vertical growth in the country. One of the most startling facts is that many Chinese commercial skyscrapers have been built in smaller cities, and are more likely than residential skyscrapers to be built farther from central business districts, a pattern that is reversed in other countries such as the U.S. This suggests that factors outside of the competitive market framework could be at play. Indeed, we identify government intervention as a significant force in China's skyscraper development. This has not only contributed to the sheer number of skyscrapers, but might also have distorted their location choices. We show

[33]https://www.scmp.com/economy/china-economy/article/3168678/chinas-urbanisation-push-could-be-bottleneck-slowest

[34]See https://www.vice.com/en/article/epn3bp/china-demolition-building-kunming for examples of unfinished high-rises.

[35]See https://www.reuters.com/breakingviews/markets/asia/chinas-next-debt-crisis-will-be-municipal-2022-01-10/ for another example.

that local governments have granted sizable subsidies to commercial skyscraper projects, in the form of price discounts on land for construction. These discounts have generally been provided for projects in smaller cities or in suburban districts, by leaders with stronger career incentives, and during the central government's credit expansion period.

By quantifying the economic impacts of skyscrapers, we also empirically assess the validity of the policy rationales behind government intervention in skyscraper development: as suggested by policy documents, local officials encourage high-rise commercial buildings to boost urban growth in their jurisdictions, which they hope will increase their chances of promotion and increase land revenues. However, we find that in marked contrast to the large, localized positive spillovers near non-subsidized skyscrapers, subsidized skyscrapers yield much less of a spillover effect in terms of a land price premium, new business development, or endogenous urban amenities 5 to 10 years after their completion. We show that the lack of these spillovers around subsidized skyscrapers is caused by a mix of their poor locations, less reliable developers, and inadequate supporting infrastructure.

Our findings call into question the presumption that heavily subsidizing skyscrapers confers significant benefits, such as attracting businesses and promoting land revenue. One important implication is that the spillovers of grand projects such as skyscrapers are highly dependent on local factors. In our view, the fact that such policies work *somewhere* does not guarantee that they work *everywhere*. Moreover, the fiscal motive for placing these projects within large tracts of undeveloped land, and the corresponding lack of supporting infrastructure and subsequent investments, further jeopardize their economic impacts.

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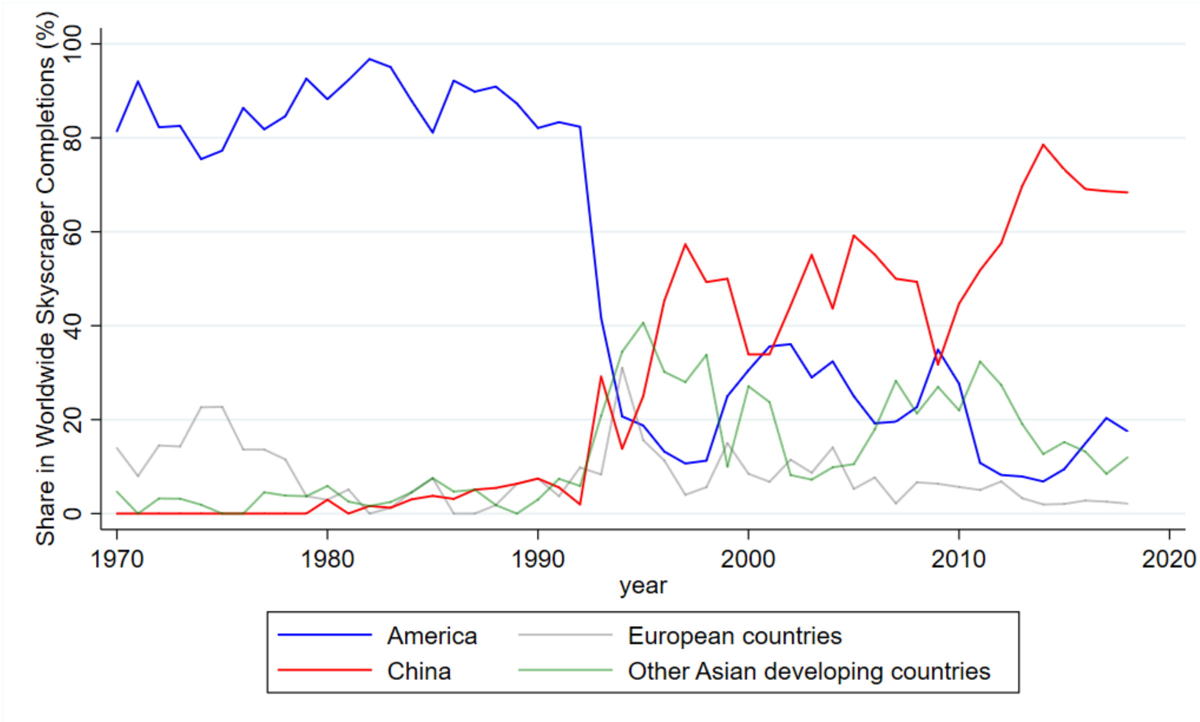


Figure 1: Trend of Worldwide Commercial Skyscraper Completions

Notes: This figure displays the evolution of annual skyscraper completions in China, the U.S., major European nations (Belgium, France, Germany, Italy, the Netherlands, Poland, and Spain), and other developing economies in Asia (India, Indonesia, Kuwait, Malaysia, the Philippines, Qatar, Thailand, the United Arab Emirates, and Vietnam). A skyscraper is defined as a high-rise commercial building over 100m high, according to the "Uniform Standard for Design of Civil Buildings: GB 50352-2019" issued by China's Ministry of Housing and Urban–Rural Development.

Sources: the Global Tall Building Database of the CTBUH and Emporis.

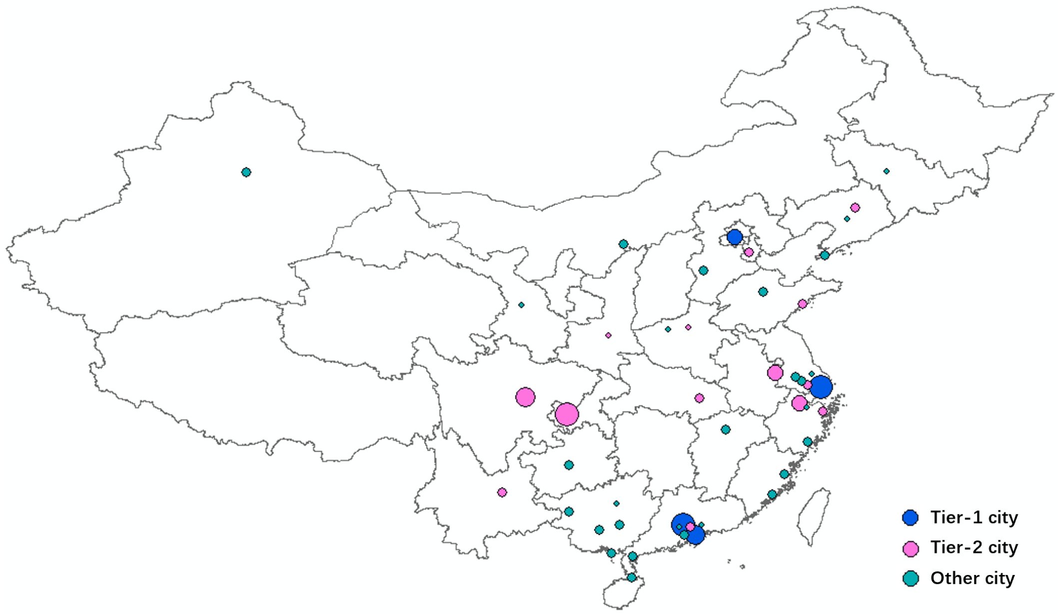


Figure 2: Geographic Distribution of Newly Completed Commercial Skyscrapers in China, 2006–2014

Notes: Each circle represents a skyscraper city, and the size of the circle is proportional to the number of skyscrapers built therein. On the color-coded map, 56 Chinese cities are further divided into multiple tiers based on their levels of economic development (Zheng and Kahn, 2013; Glaeser et al., 2017).

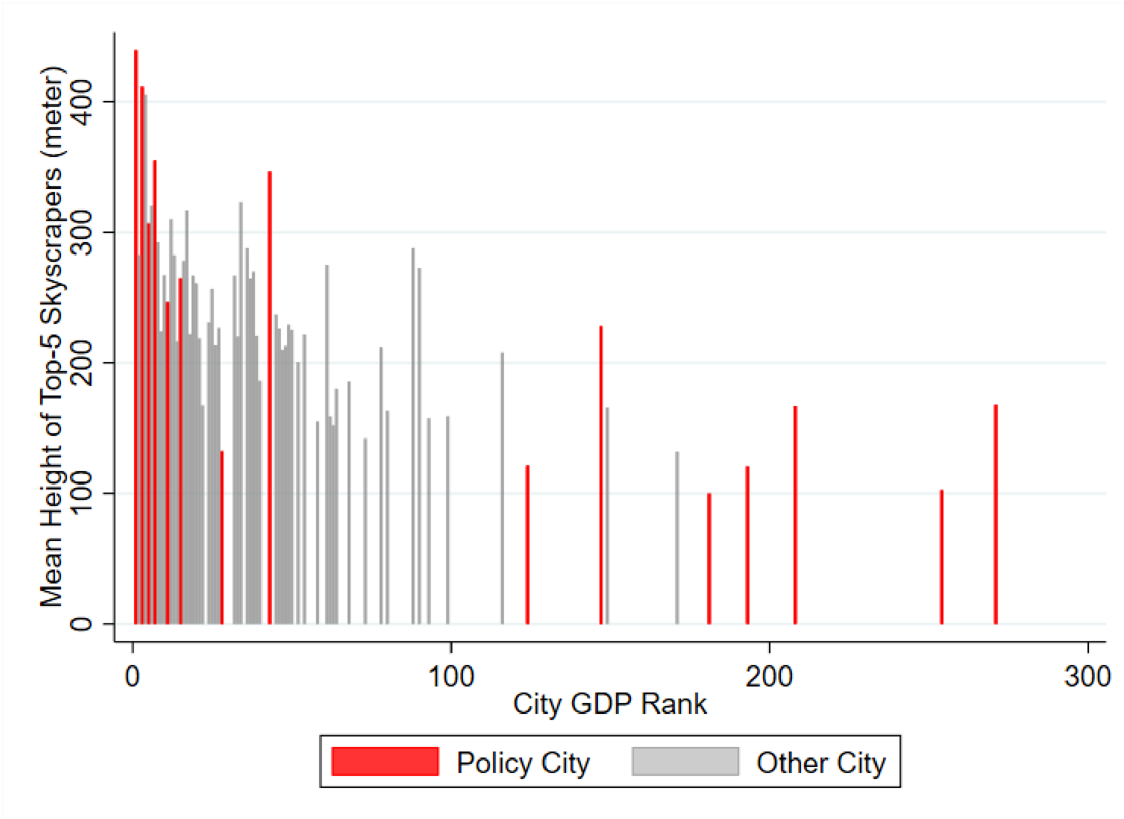
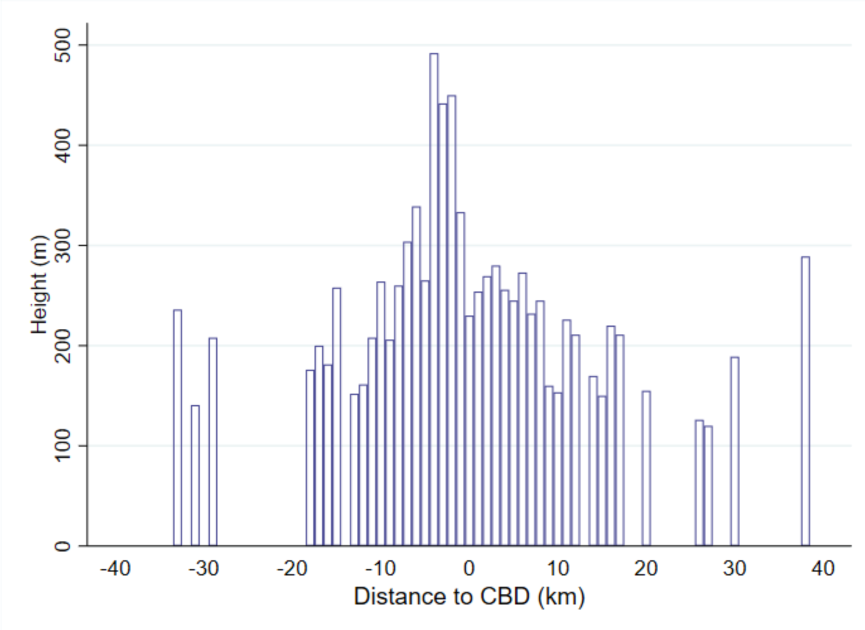
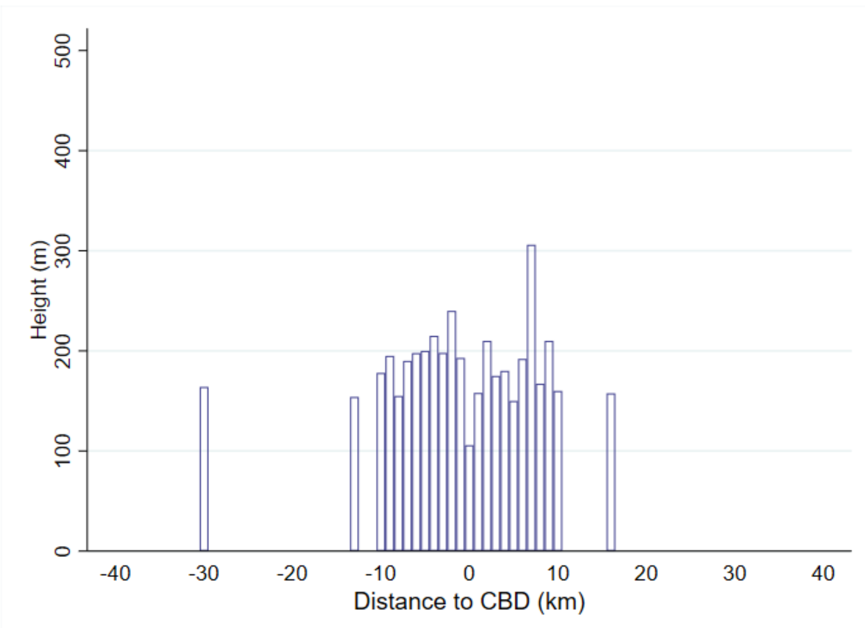


Figure 3: Commercial Skyscraper Heights, City GDP Rank and Policy Support, 2010

Notes: This figure plots the average height of the top 5 tallest skyscrapers in each Chinese city against the city's GDP rank (2010) in ascending order. The red bars depict those cities that have issued policies that encourage the development of local skyscrapers (see Table A4 for details).



(a) Commercial Skyscrapers

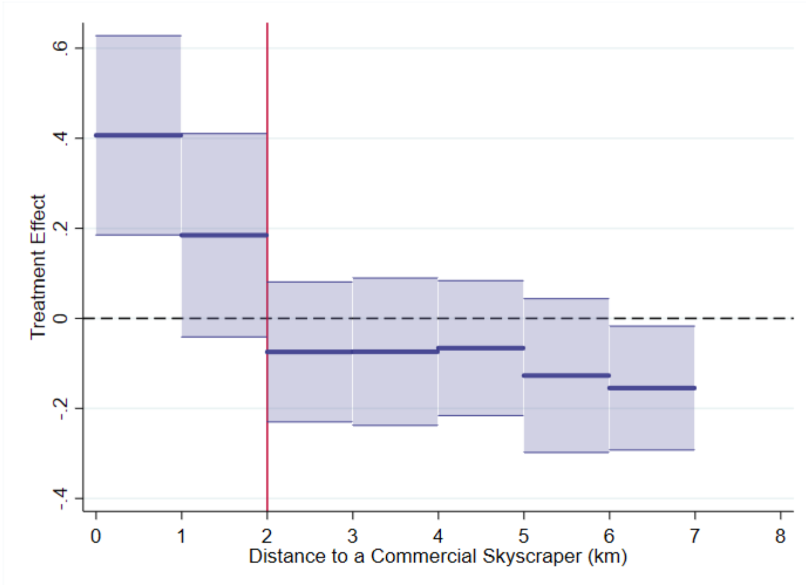


(b) Residential Skyscrapers

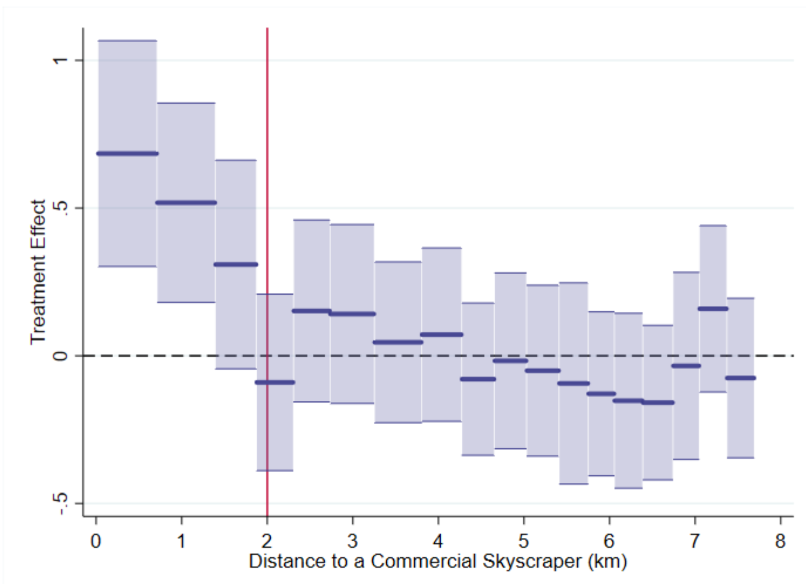
Figure 4: Distribution of Skyscrapers by Distance from the CBD, 2006–2014

Notes: In panel (a), each bar represents the height of the tallest commercial skyscraper within a 1km bin to the west or east of the CBD across 56 Chinese cities with skyscrapers. In panel (b), each bar represents the height of the tallest residential building. Negative (positive) distance values indicate a location in the west (east) where the skyscraper's x-coordinate in the World Mercator projection is smaller (larger) than the x-coordinate of the CBD.

Sources: the Global Tall Building Database of the CTBUH.



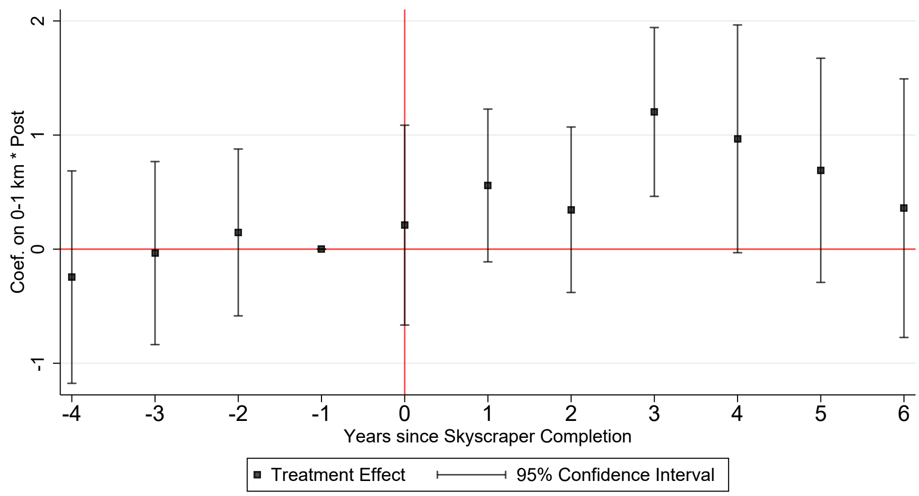
(a) 1-km Rings



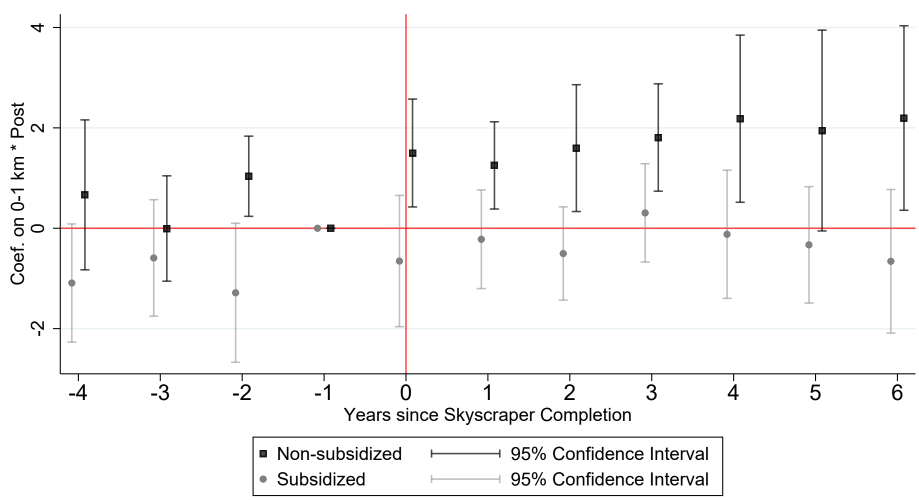
(b) 20 quantile-spaced intervals

Figure 5: Spatial Spillover Effects on Land Value by Distance to a Commercial Skyscraper

Notes: This figure plots the spatial impacts of commercial skyscrapers on the land value of nearby plots. Panel (a) depicts the estimates from Equation (2), whereby each bar represents the coefficient on a 1-km ring, and land parcels located in the 8^{th} ring (7–8 km away from the skyscraper) serve as the reference group. Panel (b) follows Butts (2023) by dividing all parcels within 8 km of a skyscraper into 20 equally-partitioned intervals, whereby each bar represents the coefficient on an interval, with parcels in the $19-20^{th}$ quantile serving as the reference group. The horizontal dashed line (in dark blue) depicts the point estimate for each distance bin, and the shaded areas plot the 95% confidence intervals.



(a) Land Value (all commercial skyscrapers)



(b) Land Value (subsidized vs. unsubsidized commercial skyscrapers)

Figure 6: Event Study: Commercial Skyscrapers' Impacts on Nearby Land Value

Notes: This figure plots the estimates on $\beta^P_{1,t}s$ for the 11-year event window based on Equation (3). The omitted category $t = -1$ is the year prior to the skyscraper's completion. Panel (a) displays the estimates of the dynamic spillovers from all commercial skyscrapers. Panel (b) displays the estimates from unsubsidized (black squares) and subsidized (grey circles) commercial skyscrapers separately. The effects on parcels sold more than 6 years after the skyscraper's completion are categorized into the event window "6 (plus)" and not reported, and those sold more than 4 years prior to completion are categorized into the event window "-4 (minus)" and not reported. The capped spikes (I-beams) plot the 95% confidence interval for the estimates.

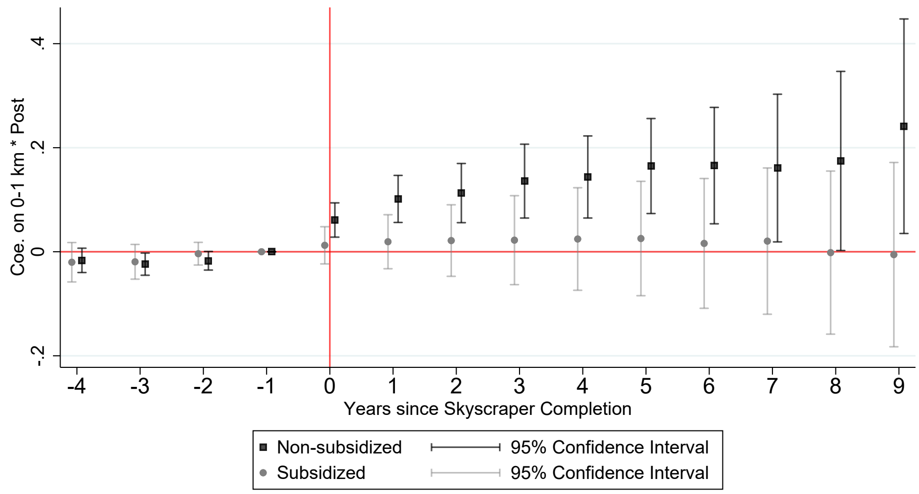


Figure 7: Event Study: Commercial Skyscrapers' Impacts on Local Firm Registrations

Notes: This figure plots the estimates on $\beta^P_{1,t}s$ for the 14-year event window based on Equation (5), where the dependent variable is the log number of the newly-registered firms in each 1km×1km grid–cell, obtained from annual firm registration records (2003-2018). The omitted category $t = -1$ is the year prior to the skyscraper's completion. Estimates of the dynamic spillovers from unsubsidized (black squares) and subsidized (grey circles) commercial skyscrapers are separately reported. The effects on parcels sold more than 9 years after the skyscraper's completion are categorized into the event window "9 (plus)" and not reported, and those sold more than 4 years prior to the completion of the skyscraper are categorized into the event window "-4 (minus)" and not reported. The capped spikes (I-beams) plot the 95% confidence interval for the estimates.

Table 1: Descriptive Statistics

Variable	Mean	SD	10^{th} pct	Median	90^{th} pct
Panel A. Skyscraper Data 2006-2014 (545 obs.)					
Commercial Skyscraper (Dummy)	0.8	0.4	0	1	1
Height (m)	188.2	52.7	133	180	250
Construction Duration ($year$)	3	1	2	3	4
Panel B. Land Transaction Records 2003-2017 (234235 obs.)					
Price (RMB/m^2)	1576.8	2860.9	59.8	554.6	3986
Parcel Size (m^2)	12689.6	21710.6	19.8	938	46710.4
Land Use (1, commercial use; 0, residential use)	0.2	0.4	0	0	1
Land Evaluation Grade (1-15)	3	3	1	3	8
Distance to CBD (km)	16.5	26.9	1.5	6.1	49.3
Floor Area Ratio	2.3	1.4	0.4	2	4.5
Transaction Method: English Auction (Dummy)	0.1	0.3	0	0	0
Transaction Method: Two-stage Auction (Dummy)	0.3	0.5	0	0	1
Transaction Method: Bilateral Agreement (Dummy)	0.6	0.5	0	1	1
Transaction Method: Invited Auction (Dummy)	0	0.1	0	0	0
Distance to Public Park (km)	9.1	12.4	0.5	3.2	27.2
Distance to Rail Station (km)	22.9	23.1	2.5	14.5	57.3
Commercial Skyscraper Land (Dummy)	0.002	0.05	0	0	0
Panel C. Gridcell-level Firm Registration Data 2003-2018 (125186 obs.)					
# of Firms in each 1km×1km Gridcell	13.1	96.8	0	4	26
Panel C. Gridcell-level Business Amenity Data 2010-2017 (55186 obs.)					
# of Business Amenities in each 1km×1km Gridcell	113.4	370.6	2	14	251
Panel D. Ring-level Public Land Data (5019 obs.)					
# of Public Parcels	11.2	32.9	0	1	23
Panel E. Developer Information (228 obs.)					
Dishonest Judgment Debtor (Dummy)	0.2	0.4	0	0	1
# of Involved Lawsuits	244.8	574.3	2	58	596
Cash–to–debt Ratio <100% (Dummy)	0.1	0.3	0	0	0
Debt–to–equity Ratio >100% (Dummy)	0.3	0.5	0	0	1
Debt–to–asset Ratio >70% (Dummy)	0.5	0.5	0	0	1

Notes: This table summarizes the descriptive statistics of relevant variables used in our empirical analyses.

Table 2: Average Land Price Discounts to Skyscrapers: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dep. Variable: Log Land Transaction Price						
Commercial Skyscraper Land	-0.377***	-0.449***	-0.512***			
	(0.144)	(0.132)	(0.125)			
Residential Skyscraper Land				0.177	0.0696	0.0338
				(0.144)	(0.133)	(0.162)
Observations	8692	5618	3171	9176	4614	1751
Adjusted R^2	0.335	0.373	0.405	0.546	0.545	0.421
Panel B: Dep. Variable: Log Land Auction Reserve Price						
Commercial Skyscraper Land	-0.447**	-0.519***	-0.647***			
	(0.193)	(0.182)	(0.178)			
Residential Skyscraper Land				0.00661	0.0630	-0.0890
				(0.173)	(0.159)	(0.164)
Observations	7344	4607	2545	6290	3037	1047
Adjusted R^2	0.508	0.526	0.578	0.612	0.610	0.636
Matching radius	$[\leq 10km]$	$[\leq 5km]$	$[\leq 2.5km]$	$[\leq 10km]$	$[\leq 5km]$	$[\leq 2.5km]$
Matched pair Observations	$[\geq 3]$	$[\geq 3]$	$[\geq 3]$	$[\geq 3]$	$[\geq 3]$	$[\geq 3]$
Matched pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Spatial trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β_1^D from Equation (1). The dependent variables are the logarithm of the land transaction price (Panel A) and the logarithm of the land auction reserve price (Panel B). Columns 1–3 report the coefficients from regressions using matched samples within the 10km, 5km and 2.5km radius of the commercial skyscraper, respectively. Columns 4–6 repeat the regression analyses on residential skyscrapers. Each matched pair has at least 3 observations for the sake of statistical power. The control variables include parcel characteristics such as the logarithm of the parcel size and its square, the transaction method (English auction, two-stage auction, bilateral agreement, or invited auction), the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, access to public amenities (the logarithm of the distance to the nearest public park and rail station), and a spatial trend (the latitude and longitude differences between the parcel and skyscraper × year trend). All regressions include matched pair and year fixed effects. Robust standard errors clustered at the matched pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Heterogeneous Land Price Discounts for Commercial Skyscrapers

Dep. Variable	Log Land Transaction Price					
	(1)	(2)	(3)	(4)	(5)	(6)
Commercial Skyscraper Land	-0.574***	-0.358**	-0.445***	-0.519***	-0.553*	-0.451**
	(0.193)	(0.140)	(0.125)	(0.133)	(0.302)	(0.174)
Panel A: Political Incentive Explanation						
Commercial Skyscraper Land * **1**{Mayor Incentive}	-0.591**					
	(0.300)					
Commercial Skyscraper Land * **1**{Secretary Incentive}	0.159					
	(0.227)					
Commercial Skyscraper Land * **1**{4-trillion Plan}		-0.534*				
		(0.274)				
Panel B: Alternative Explanations						
Commercial Skyscraper Land * Corruption Cases			-0.0240			
			(0.0353)			
Commercial Skyscraper Land * **1**{Anti-corruption Campaign}				0.0862		
				(0.248)		
Commercial Skyscraper Land * **1**{SOE}					0.214	
					(0.326)	
Commercial Skyscraper Land * **1**{POE}					-0.0202	
					(0.342)	
Commercial Skyscraper Land * **1**{Local}						-0.154
						(0.215)
lndis 5_no2	[$\leq 2.5km$]	[$\leq 2.5km$]	[$\leq 2.5km$]	[$\leq 2.5km$]	[$\leq 2.5km$]	[$\leq 2.5km$]
Matched pair Observations	[≥ 3]	[≥ 3]	[≥ 3]	[≥ 3]	[≥ 3]	[≥ 3]
Matched pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Spatial trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3171	3171	3171	3171	3171	3171
Adjusted R^2	0.406	0.406	0.405	0.405	0.405	0.405

Notes: Using a spatially matched sample within a 2.5km radius of the skyscraper, column 1 interacts the skyscraper land dummy with measures of the city mayor and party secretary's career-incentive intensity, whereby this measure switches to 1 if the career-incentive intensity estimated in Table A6 is above the sample mean. Column 2 interacts the skyscraper land dummy with a dummy indicator for the "4 trillion economic stimulus plan," which equals 1 if the transaction took place after 2009 and in a city where commercial lending grew faster than the national average between 2007 and 2012. Column 2 additionally controls a dummy for the "post-crisis era" which equals 1 if the skyscraper was built after 2008. Column 3 introduces an interaction term between the dummy for commercial skyscraper land and the city-level cumulative number of corruption cases involving land officials between 2010 and 2016. Column 4 interacts the commercial skyscraper land dummy with an indicator for the anti-corruption campaign. This indicator equals 1 if the land transaction took place after 2012 when the Eight-Point Stipulations were implemented, following Chen and Kung (2019). Columns 5–6 interact the commercial skyscraper land dummy with measures indicating the developer's background. In column 5, the indicator variable "SOE" equals 1 if the developer is a state-owned enterprise. The indicator variable "POE" equals 1 if the developer is a privately-owned enterprise. Foreign-owned enterprises serve as the reference. In column 6, the indicator variable "Local" equals 1 if the developer is a local enterprise, and non-local developers serve as the reference. Each matched pair has at least 3 observations for the sake of statistical power. The control variables include parcel characteristics such as the logarithm of the parcel size and its square, the transaction method (English auction, two-stage auction, bilateral agreement, or invited auction), the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, access to public amenities (the logarithm of the distance to the nearest public park and rail station), and a spatial trend (the latitude and longitude differences between the parcel and the skyscraper × the year trend). All regressions include matched pair and year fixed effects. Robust standard errors clustered at the matched pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Economic Impacts of Commercial Skyscrapers: More Subsidies, More Spillovers?

Dep. Variable	Log Land Value					
	(1)	(2)	(3)	(4)	(5)	(6)
0-1 km * Post	0.493***	0.488***	0.696***	1.246***	1.493***	1.181***
	(0.169)	(0.172)	(0.222)	(0.242)	(0.248)	(0.248)
1-2 km * Post	0.267*	0.280*	0.363**	0.539**	0.480	0.481*
	(0.155)	(0.152)	(0.153)	(0.256)	(0.341)	(0.245)
0-1 km * Post * Subsidy Rate				-1.476**		
				(0.692)		
1-2 km * Post * Subsidy Rate				-0.653		
				(0.631)		
0-1 km * Post * **1**{Subsidy>0}					-1.094***	
					(0.327)	
1-2 km * Post * **1**{Subsidy>0}					-0.288	
					(0.392)	
0-1 km * Post * **1**{Subsidy>0 (significant)}						-0.792**
						(0.369)
1-2 km * Post * **1**{Subsidy>0 (significant)}						-0.293
						(0.336)
Control group	[2-3km]	[2-3km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]
Skyscraper matched sample–year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skyscraper matched sample–ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Parcel charac.	Yes	Yes	Yes	Yes	Yes	Yes
Spatial trend	No	Yes	Yes	Yes	Yes	Yes
Joint coefficient ($\beta_1 + \beta_1 * Subsidy$)					0.399	0.388
Prob > F ($\beta_1 + \beta_1 * Subsidy$=0)					0.10	0.15
Observations	3301	3301	3004	2015	2015	2015
# of Skyscrapers	293	293	281	148	148	148
Adjusted R^2	0.260	0.264	0.187	0.331	0.332	0.331

Notes: This table reports estimates of β_r^P from Equation (3). Using a spatially matched sample within a 3km radius of the skyscraper, column 1 reports the treatment coefficients on the two concentric rings (0–1km) and (1–2km) while using the 2–3km ring as the control group. Column 2 further considers the within-ring variation by adding the spatial trend (the latitude and longitude differences between the parcel and the skyscraper × the year trend). Column 3 conducts a donut analysis, using an alternative sample within a 4km radius of the skyscraper but excluding parcels in the 2–3km buffer ring. Column 4 interacts the treatment indicators with the estimated subsidy rate. Column 5 interacts the treatment indicators with a subsidy dummy (which equals 1 if the subsidy rate is larger than zero). Column 6 interacts the treatment indicators with a subsidy dummy, which equals 1 if the land subsidy rate is significantly higher than zero (for each commercial skyscraper, we perform a one-sample T-test, calculating the mean price difference between commercial skyscraper land and non-skyscraper land as well as its significance level). The land parcel characteristics include the logarithm of the parcel size and its square, the transaction method, the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, and access to public amenities, as previously defined. All regressions include skyscraper matched sample-year and skyscraper matched sample-ring fixed effects. Standard errors are clustered at the skyscraper level and reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Economic Impacts of Commercial Skyscraper: Alternative Outcomes

Dep. Variable	Log (# of Newly-registered Firms+1)			Log (# of Business Amenities+1)		
	(1)	(2)	(3)	(4)	(5)	(6)
0-1 km * Post	0.0637***	0.0929***	0.0958***	0.351***	0.428***	0.356***
	(0.0150)	(0.0208)	(0.0210)	(0.0644)	(0.109)	(0.123)
1-2 km * Post	-0.00104	0.0128	0.0192	0.256***	0.237**	0.190**
	(0.0141)	(0.0200)	(0.0204)	(0.0506)	(0.0878)	(0.0886)
0-1 km * Post * Subsidy Rate		-0.0945**			-0.468***	
		(0.0406)			(0.151)	
1-2 km * Post * Subsidy Rate		-0.0450			-0.237*	
		(0.0368)			(0.123)	
0-1 km * Post * **1**{Subsidy>0 (significant)}			-0.0721**			-0.257*
			(0.0301)			(0.132)
1-2 km * Post * **1**{Subsidy>0 (significant)}			-0.0454			-0.104
			(0.0279)			(0.0992)
Control group	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]
Skyscraper matched sample–year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid–cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid–cell by year time trend	Yes	Yes	Yes	Yes	Yes	Yes
Joint coefficient ($\beta_1 + \beta_1 * Subsidy$)			0.024			0.099
Prob > F ($\beta_1 + \beta_1 * Subsidy$=0)			0.27			0.18
Observations	34424	34424	34424	13896	13896	13896
Adjusted R^2	0.991	0.991	0.991	0.867	0.860	0.860

Notes: This table reports the estimated spillover effects of commercial skyscrapers on alternative outcomes, using Equation (5). In Columns 1–3, the dependent variable is the logarithm of (the number of newly-registered firms + 1) calculated at the 1km×1km grid-cell level. In Columns 4–6, the dependent variable is the logarithm of (the number of business amenities including restaurants, banks, educational institutions, hotels, and retail facilities + 1) at the 1km×1km grid-cell level. Columns 1 and 4 show the baseline results. Columns 2 and 5 further include the interaction term between the treatment indicators and the subsidy rate measure. Columns 3 and 6 add the interaction term between the treatment indicators and a subsidy dummy (indicating significant and positive subsidy received, as previously defined). Grid-cells located within 0–1km or 1–2km of a commercial skyscraper are the treatment group, and those in the 3–4km buffer ring serve as the control group. Commercial skyscrapers without subsidy information are removed from the working sample. All regressions include skyscraper matched sample–year fixed effects, grid-cell fixed effects, and a grid-cell–year time trend. Standard errors are clustered at the grid-cell level and reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Economic Impacts of Commercial Skyscrapers on Public Land Parcel Supply

Dep. Variable	Log (# of Public Parcels+1)		
	(1)	(2)	(3)
0-1 km * Post	0.215***	0.312***	0.297***
	(0.0659)	(0.0672)	(0.0652)
1-2 km * Post	0.246***	0.282***	0.277***
	(0.0584)	(0.0916)	(0.0908)
0-1 km * Post * Subsidy Rate		-0.265**	
		(0.125)	
1-2 km * Post * Subsidy Rate		-0.103	
		(0.154)	
0-1 km * Post * **1**{Subsidy>0 (significant)}			-0.161*
			(0.0904)
1-2 km * Post * **1**{Subsidy>0 (significant)}			-0.0647
			(0.102)
Control group	[3-4km]	[3-4km]	[3-4km]
Skyscraper matched sample–year FE	Yes	Yes	Yes
Skyscraper matched sample–ring FE	Yes	Yes	Yes
Joint coefficient ($\beta_1 + \beta_1 * Subsidy$)			0.136
Prob > F ($\beta_1 + \beta_1 * Subsidy$=0)			0.14
Observations	3167	3167	3167
Adjusted R^2	0.218	0.220	0.219

Notes: This table reports estimates of the impacts of commercial skyscrapers on the supply of public land parcels nearby from Equation (6). The dependent variable is the logarithm of (the number of public land parcels designated for the development of public transit, schools, cultural and sports facilities, and hospitals + 1) within each 1km ring. Column 1 reports the baseline results. Column 2 further includes the interaction term between the treatment indicators and the subsidy rate. Column 3 adds the interaction term between the treatment indicators and the subsidy dummy (indicating significant and positive subsidy received, as previously defined). The 0–1km or 1–2km ring surrounding a commercial skyscraper is the treatment group, while the 3–4km buffer ring serves as the control group. Commercial skyscrapers without subsidy information are removed from the working sample. All regressions include skyscraper matched sample–year fixed effects and skyscraper matched sample–ring fixed effects. Standard errors are clustered at the skyscraper matched sample level and reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Commercial Skyscraper Spillovers: Potential Channels

	Ex ante: Developer Quality					*Ex post*: Developing Efficiency
Dep. Variable	Log (# of Law Suits+1) (1)	Dishonest Judgment Debtor (2)	DTA >70% (3)	DTE >100% (4)	CTD <100% (5)	Construction Duration (6)
Subsidy Rate	0.388*	0.138**	0.0869	0.139	0.111**	0.250*
	(0.199)	(0.0519)	(0.0801)	(0.200)	(0.0435)	(0.134)
Observations	228	228	137	137	137	228
Adjusted R^2	0.132	0.111	0.098	0.051	0.080	0.036

Notes: This table reports the bivariate relationship between the subsidy received and the developer's quality. *Ex ante* developer quality is measured using five financial performance variables. In Column 1, the dependent variable is the logarithm of (the number of lawsuits the developer was involved in + 1). In Column 2, the dependent variable is a dummy indicator which equals 1 if the developer was listed among dishonest judgment debtors. In Columns 3–5, the dependent variables are three financial performance indicators: dummy variables indicating a debt-to-asset (DTA) ratio of greater than 70%, a debt-to-equity (DTE) ratio of greater than 100%, and a cash-to-debt (CTD) ratio of not greater than 100%, respectively. *Ex post* developing efficiency is measured as the construction duration of each skyscraper project. In Column 6, the dependent variable is the residual obtained from regressing construction duration on the city covariate (including soil condition measured by city-level seismic precautionary intensity) and skyscraper characteristics (including building height and size of the land parcel for building construction). Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Linking Potential Channels to Commercial Skyscraper Spillovers

Dep. Variable	Log Land Value					
	(1)	(2)	(3)	(4)	(5)	(6)
Reduced-form Analysis						
0-1 km * Post	1.246***	0.0564	0.974***	0.437	0.0726	-2.504*
	(0.242)	(0.802)	(0.305)	(0.614)	(0.583)	(1.271)
0-1 km * Post * Subsidy Rate	-1.476**	-1.391*	-1.274*	-1.413**	-1.129	-0.784
	(0.692)	(0.733)	(0.707)	(0.663)	(0.695)	(0.768)
Panel A: Locational Advantages						
0-1 km * Post * **1**{Tier 1/2 City}		1.182*				0.611
		(0.682)				(0.683)
0-1 km * Post * **1**{CBD}			0.566*			0.550*
			(0.333)			(0.320)
0-1 km * Post * Public Parks and Rail Stations				0.152		0.312***
				(0.114)		(0.120)
Panel B: Government-led Complementary Investment						
0-1 km * Post * Public Land Parcels					0.466**	0.484**
					(0.215)	(0.212)
Observations	2015	2015	2015	2015	2015	2015
Adjusted R^2	0.331	0.330	0.331	0.330	0.331	0.330
Mediation Analysis						
Average Controlled Direct Effect		-1.341*	-1.271*	-1.349**	-1.102	-0.684
		[0.688]	[0.676]	[0.675]	[0.682]	[0.659]
Size Relative to Main Effect		90.85%	86.11%	91.39%	74.66%	44.78%
Control group	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]
Skyscraper matched sample–year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skyscraper matched sample–ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Spatial trend	Yes	Yes	Yes	Yes	Yes	Yes

Notes: A reduced-form heterogeneity analysis links the three potential channels to commercial skyscrapers' spillover effects. Column 1 repeats the baseline estimates of column 4 in Table 4 for reference. Column 2 adds the interaction term between the treatment indicators and the city size measure. This measure equals 1 if the skyscraper city is categorized as tier 1 or tier 2 (Glaeser et al., 2017). Column 3 interacts the treatment indicators with the skyscraper's within-city location. This measure equals 1 if the skyscraper was built in the CBD. Column 4 interacts the treatment indicators with the number of public parks and rail stations within a 5km radius of the skyscraper. Column 5 interacts the treatment indicators with the cumulative number of public land parcels supplied by the local government during the 2003–2017 period. Column 6 combines the interactions used in columns 2–5. A mediation analysis follows the two-step approach proposed by Acharya et al. (2016), and the average controlled direct effect (ACDE) is reported. The control variables include a spatial trend and land parcel characteristics—the logarithm of the parcel size and its square, the transaction method, the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, and access to public amenities, as previously defined. All regressions include skyscraper matched sample–year and skyscraper matched sample–ring fixed effects. Standard errors are clustered at the skyscraper matched sample level and reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix

A1 Additional Data Details

Policy Documents In this section, we first describe how we conducted the search to collect government documents that show preferential treatment of commercial skyscraper construction projects, then we discuss the main aspects of these policies.

We started with a few policy documents that promoted skyscraper construction, which were sourced from the official websites of two cities, Baise and Qinzhou. Motivated by this selective sample, we set out to identify four frequently appearing keywords: "skyscraper," "100 meters," "preferential," and "encourage" (or synonyms such as "tall building" and "support"). Using those keywords, we then performed an intensive search of similar policy documents from other cities by querying Baidu, the largest Chinese search engine. After manually removing non-government web pages, we were left with 31 relevant policy documents issued by 22 cities. Finally, to ensure the completeness of these data, we queried the China Law Journal Database (Beidafabao, in Chinese) maintained by the Legal Information Center of Peking University, which hosted the entire corpus of more than 5,000 policies and transcripts of government announcements. We conducted an extensive analysis using the same set of keywords as we had used in the search, and identified 1,673 raw documents of interest. To narrow down the relevant reports from this large sample, we used a deep learning algorithm, *doc2vec*, which transformed each corpus of documents (the one from Beidafabao and the one from Baidu) into a vector. We further measured the similarity between the Beidafabao and Baidu documents as the cosine of the angle between the two corresponding vectors (Le and Mikolov, 2014). We then revisited all of those documents from Beidafabao with a similarity index larger than 30%. The process yielded 23 additional related policy documents which we had not identified using Baidu, bringing the total number of observations to 54 policies from 28 cities in China, as documented in Table A4. Overall, this suggests that the sum of the documents from the two sources is more comprehensive.

By moving across columns, the table allows us to zoom in on the four key elements often included in these policy documents and observe them alongside the cities' GDP rank. In particular, Column 3 illustrates that many policies specify the skyscraper land discount terms and the conditions for obtaining them. Column 4 shows that a large majority include tax reductions. Column 5 suggests that a considerable number of cities explicitly lay out the goal of new town development in their documents. Column 6 shows whether or not the policies restrict the policy support to only those skyscrapers that serve a commercial function.

City Leader Data To evaluate the career incentives of Chinese city leaders, we collect demographic and career information for mayors and city party secretaries from the Chinese Political Elite Database.[36] The data set includes their date of birth, start and end time in office, hierarchical level at the start of their term (prefecture level, deputy province level, or higher), educational attainment, and status after leaving office (lateral move, promotion, retirement, or other). We extracted the complete records of 1646 mayors and 1600 party secretaries who were in office between 2003 and 2015. We then merged this data with information on skyscrapers using the project approval time, which we inferred from the transaction time of the land on which the skyscrapers were built.

Developer Quality To evaluate the quality of each developer, we employed two data sources. The first source is firm registration data collected by the State Administration for Industry and Commerce spanning 2003 to 2018. This dataset includes information on the risks of operation for the developers of 288 skyscraper projects, as measured by the number of lawsuits in which they were involved and whether they were listed among dishonest judgment debtors. The second source is the national tax survey, which was conducted between 2007

[36] Data source link: www.junyanjiang.com/data.html.

and 2016 by the Ministry of Finance and the State Administration of Taxation. We measure a developer's financial conditions using three indicators (debt-to-asset, debt-to-equity, and cash-to-short-term borrowing ratio). However, due to the limited coverage of the survey, we only have data for 137 skyscraper developers.

A2 Patterns of Chinese Skyscraper Development

According to neoclassical theory, land–capital substitution in building service production is the fundamental driver of skyscraper development (Epple et al., 2010; Ahlfeldt and Barr, 2022): height is substituted for expensive land in a purely economic sense. Urban land value rises with proximity to the CBD, and increases with city size and density (Albouy, 2008; Albouy et al., 2018; Combes et al., 2019). Thus, if land–capital substitution is indeed the most important driving force behind high-rise development, skyscrapers should be more likely to be built in large cities and near CBDs. Below we document several stylized facts comparing skyscraper development across countries, and illustrate that the pattern of the most recent wave of skyscraper construction in China has deviated from the predictions of classic urban models and contrasts with those of developed countries.

A2.1 Relationships Between Building Height and City Population

We begin by presenting global patterns of skyscraper development. Figure A1 plots the relationship between city size and the mean height of the 10 tallest buildings in each of 117 cities in four regions: the United States, Europe, China, and other developing economies in Asia. We find substantial deviation in skyscraper construction across countries. Specifically, the figure indicates a strong relationship between population and skyscraper height in the U.S. and Europe: an increase of 10 million in metro population predicts an additional 270m increase in the average skyscraper height in the U.S. and 250m in Europe. This pattern is consistent with land–capital substitution: urban land value tends to increase with city size, which encourages vertical building.

However, the height–city population connection is much weaker in China and other developing economies in Asia, such as the United Arab Emirates and Malaysia. The estimated coefficients are roughly half as large as those found in developed countries: when the urban population grows by 10 million, the average height of the ten tallest buildings increases by only 140m in China and 120m in other developing economies in Asia. This is also consistent with the pattern in Figure 2: skyscrapers in China are no longer concentrated in tier-1 cities or provincial capitals. A considerable proportion of the skyscraper projects from 2006 to 2014 were located in smaller cities.

A2.2 Distance Gradient: Intensive and Extensive Margins

Another prediction of land–capital substitution is that it is more economically justifiable to build skyscrapers near CBDs. In the second empirical exercise, we estimate the distance gradients of skyscrapers in China. At the intensive margin, we estimate the height–distance gradient by regressing the logarithm of skyscraper height on the logarithm of distance to the CBD and a host of other covariates. Panel A of Table A1 reports the results. In China, the estimated height–distance gradient is -0.042 for commercial skyscrapers. The point estimate is robust to alternative measures of "distance to CBD" (Columns 2 and 3). For residential skyscrapers, the height–distance gradient is around 0.049, but imprecisely estimated. Taken together, these results suggest that the height of commercial skyscrapers decreases more quickly than that of residential high-rises as one moves away from a CBD.

Turning to the extensive margin, we estimate the quantity–height gradient. To do so, we first calculate the number of skyscrapers in each 1km$\times$1km grid-cell, and then regress the logarithm of the number of skyscrapers on the logarithm of the distance from the grid-cell centroid to the CBD and a set of other covariates. The results are presented in Panel B of Table A1. The estimated quantity–distance gradient is -0.038 for commercial skyscrapers and -0.163 for residential skyscrapers, respectively. This pattern suggests that compared with residential buildings, a significant number of commercial skyscrapers have been built in locations that are farther from CBDs.

These findings corroborate the distribution of the commercial skyscrapers by distance from the CBD across Chinese cities, as shown in Figure 4. Although some of the tallest skyscrapers are located close to CBDs, many are located in suburban areas and new towns where land prices are considerably lower. In contrast, residential skyscrapers are typically more clustered in city centers.

A2.3 Land Price Elasticity of Height

To quantify how skyscraper development has responded to land costs across countries, we employ the following reduced-form empirical specification in the spirit of Ahlfeldt and McMillen (2018):

$$\ln(S_{jt}) = \alpha_t^E + \beta_1^E \ln(\hat{r_{jt}}) + \varepsilon_{jt}^E \tag{7}$$

where the dependent variable $\ln(S_{jt})$ is the logarithm of the building height of skyscraper (j) built in year (t). α_t^E denotes year fixed effects. $\ln(\hat{r_{jt}})$ is the logarithm of the predicted land value at the skyscraper site imputed based on the transaction price of nearby land parcels.[37] We use predicted land value rather than the actual transaction price of the land parcel for skyscraper construction because the latter might be heavily subsidized and thus may not reflect local fundamentals. ε_{jt}^E is a random error term.

For a meaningful cross-country comparison, we perform a parallel empirical estimation of the land price elasticity of building height in Chicago, restricting the sample to buildings over 100m that were built during the same period as the Chinese sample. Again, we conduct the analysis separately for commercial and residential skyscrapers.

[37] The predicted land value is defined as $\hat{r_{jt}}=\sum_{i=1}^{n}\left(\frac{D_{ij}^{-1}}{\sum_{i=1}^{n} D_{ij}^{-1}} \times r_{it-m}\right)$, where n represents the number of nearby land parcels with similar characteristics, D_{ij}^{-1} is the reciprocal of the Euclidean distance between land parcel (i) and skyscraper (j) $(D_{ij} < 2.5km)$, and r_{it-m} is the unit price of land parcel (i) sold $(m \in [0,3])$ years prior to the skyscraper's completion time (t).

To interpret β_1^E as the demand-side response of skyscraper construction to land cost, we need to tackle a classic simultaneity issue: unobserved supply-side factors like soil conditions might directly affect the building height and land value in tandem. To address this issue, we add the city-level seismic precautionary intensity as a control. Another concern is measurement error in the predicted land value.[38] To properly address this concern, we additionally control for the distance between the skyscraper and the land parcels used in the predictions. Further, we instrumentalize land value with demand shifters such as distance to the CBD, the neighboring public park and railway station in the Chinese sample and distance to the CBD and Lake Michigan in the Chicago sample, following the practice of Ahlfeldt and McMillen (2018).[39]

Panel A of Table A2 reports the results for China while Table A3 presents the corresponding results for the US (Chicago). In column 4, our preferred instrumental variable (IV) estimates suggest that the average elasticity of commercial skyscraper height with respect to land price is 0.057 in China, which is much smaller than in Chicago (0.188), but the estimates are similar for residential skyscrapers (0.257 and 0.169, respectively). These patterns indicate that the Sino–U.S. gap in the responsiveness of skyscraper construction to land costs cannot be driven by cross-country differences in land–capital substitution elasticity or the engineering costs associated with building up, which would generate a similar gap in the estimated height–price elasticity for residential skyscrapers as well.[40] Therefore, we

[38]We consider two main sources of measurement error. The first stems from random fluctuations in land prices, which tend to attenuate the ordinary least squares (OLS) estimate of height–price elasticity towards zero. The second source is closely related to the prediction approach. Expensive land parcels in the CBD are more likely to be underestimated if few land transactions can be observed in that neighborhood, and thus cheaper parcels farther away were used as a match. This might produce a downward bias in OLS estimates, although we further include a control variable, the distance between the CBD and land parcels, for prediction.

[39]Within-city site characteristics like distance to the CBD may be correlated with land use stringency (Brueckner et al., 2017), which may then affect building height directly. However, this effect is likely to be of limited importance; there are only two relevant cases in our sample, Beijing and Xi'an. Moreover, we use a broad range of control variables to preclude possible correlation between the instruments and the error terms.

[40]In a canonical model of tall building service production function developed by McDonald (1981) and

conclude that the substantial gap we observe is attributable to factors that lie outside the competitive market framework.

Price–height elasticity captures responses at the intensive margin. We also perform similar analyses along the extensive margin on the Chinese sample by estimating how the placement of tall buildings responds to land value, regressing the logarithm of the number of skyscrapers on predicted land value at the 1km×1km grid-cell-by-year level. Panel B of Table A2 presents the OLS and IV estimates of the extensive margin elasticities. Reassuringly, the pattern is robust: as shown in column 4, the price–quantity elasticity for commercial skyscrapers (0.0818) is much smaller than that of residential buildings (0.132).

Overall, these patterns suggest that economic fundamentals play a much less important role in driving skyscraper growth in China. Anecdotally, mayors and governors are more eager to put their cities on the map by building high-rise commercial properties. Previous studies have also pointed out that where political accountability is weak, leaders in developing countries tend to pursue private interests in such projects (Gjerløw and Knutsen, 2019). Despite these plausible alternative explanations from various contexts, in this paper we present further evidence that the spatial misallocation of skyscrapers exists not only across cities but also within them, and explore its association with government interventions in China.

A3 City-wide Analysis

Despite the lack of local spatial spillovers, some practitioners believe that the potential to promote a city's image and generate long-term, city-wide benefits constitutes a strong argument in favor of government interventions to promote skyscraper construction. At the same time, it is unclear whether such public investments stimulate real growth or merely

Ahlfeldt and McMillen (2018), the height elasticity to price is denoted by $\beta = \sigma/(1 + \theta - \lambda)$. Hence, in a competitive market framework, the magnitude of elasticity ultimately depends on three key parameters: the elasticity of land–capital substitution (σ), the elasticity of construction costs with respect to building height (θ), and the elasticity of extra space with respect to building height (λ).

reshuffle economic activities across different areas within a city.

To identify the broader impacts of skyscrapers at the city level, we collected city-level panel data between 2003 and 2015 on land prices and new establishments. Following Albouy et al. (2018), we use the land price in the CBD to ensure the measure is comparable across time and regions. For new establishments, we aggregate the firm registration records to the city-year level. We exclude cities that had constructed commercial skyscrapers before 2003 from our sample and use those that built their first commercial skyscraper after 2015 as the control group. In a DID design, we then compare a city's land value and the number of new establishments before and after skyscrapers were built using the following specification:

$$\ln(Y_{it}) = \alpha_t^C + \lambda_i^C + \beta_1^C ln(CommercialSkyscraper_{it}) + \varepsilon_{it}^C \tag{8}$$

where the dependent variable, Y_{it}, denotes city i's land value and firm registrations in year t. α_t^C are year fixed effects, which capture common macro-level shocks that affect all cities. λ_i^C are city fixed effects that account for unobserved time-invariant differences across cities that may affect the outcomes. $CommercialSkyscraper_{it}$ denotes city i's number of commercial skyscrapers in year t. Its coefficient β_1^C is the parameter of interest to be estimated, which indicates the city-wide economic impact of building more commercial skyscrapers. ε_{it}^C is the error term. Standard errors are clustered at the city level.

Columns 1 and 5 of Table A9 present the baseline estimates using Equation (8). Columns 2 and 6 add a set of additional socio-demographic variables including the logarithm of city employment, the share of residents with a university degree, and road density, which are sourced from China's Urban Statistical Yearbooks (2003–2015). The results are robust to these controls. In columns 3 and 7, we replace the continuous treatment intensity indicator with a dummy variable that equals 1 after the city has built its first commercial skyscraper, and 0 otherwise. As shown, the estimates are not sensitive to how the treatment indicator is defined. To further address the negative weights issue with staggered DID, columns 4 and 8 present the alternative Wald-DID estimators. The coefficients with different specifications are generally positive and insignificant, which suggests a weak relationship between commercial skyscraper construction and city-wide economic growth.

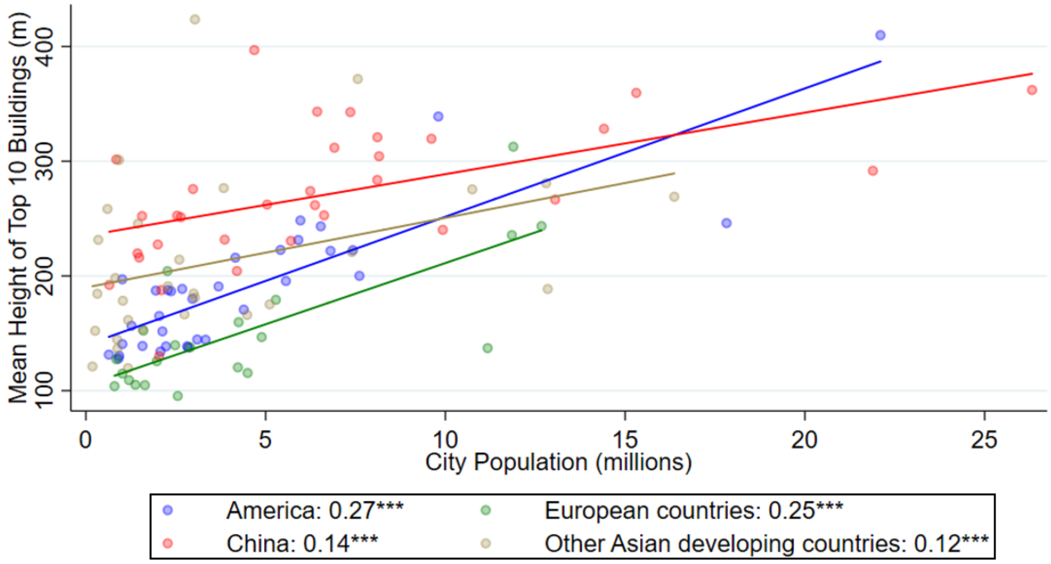


Figure A1: Skyscraper Heights and City Population: An International Comparison, 2018

Notes: This figure displays the raw relationship between a city's (metropolitan) population and the average height of its 10 tallest buildings across four sets of regions. The sample includes cities with more than 10 skyscrapers in the U.S. (34 cities), European countries (21), China (32), and other developing countries in Asia (30). The legend includes the estimated population elasticities of building height for the four regions. * significant at 10%; ** significant at 5%; *** significant at 1%.

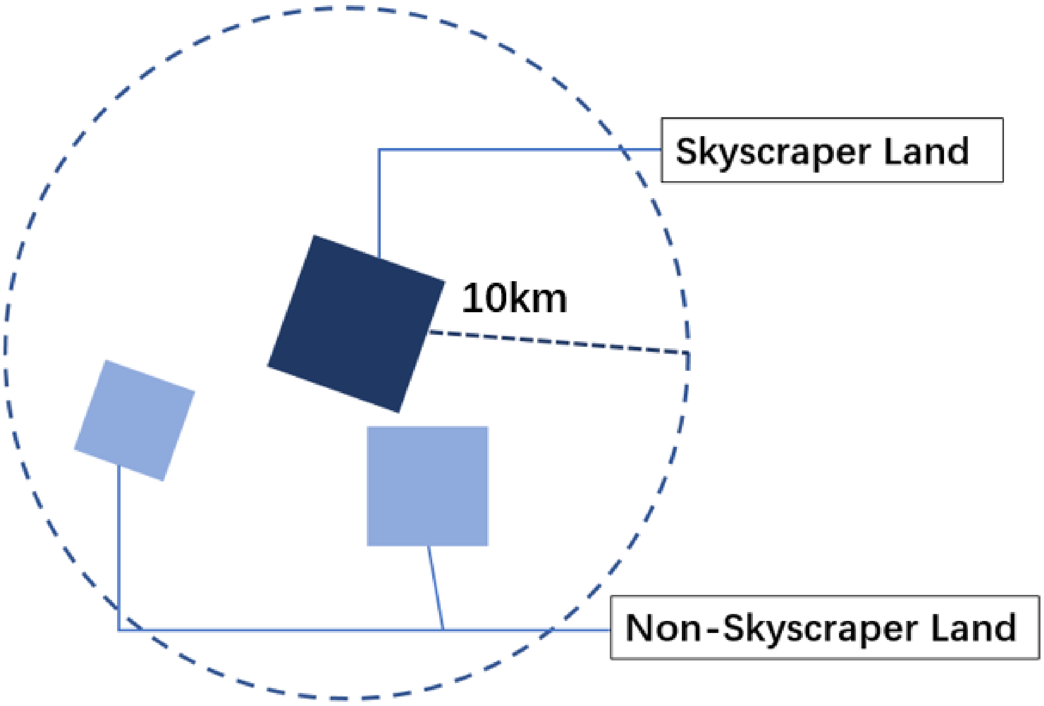


Figure A2: A Spatially Matched Sample for Quantifying Subsidies

Notes: The figure displays a spatially matched sample of transactions involving skyscraper land (in dark blue) and non-skyscraper land (in light blue). To construct the sample, we chose transactions that took place prior to the completion of the skyscraper in question. The geo-matching radius was initially set to 10km and later restricted to 5km and 2.5km.

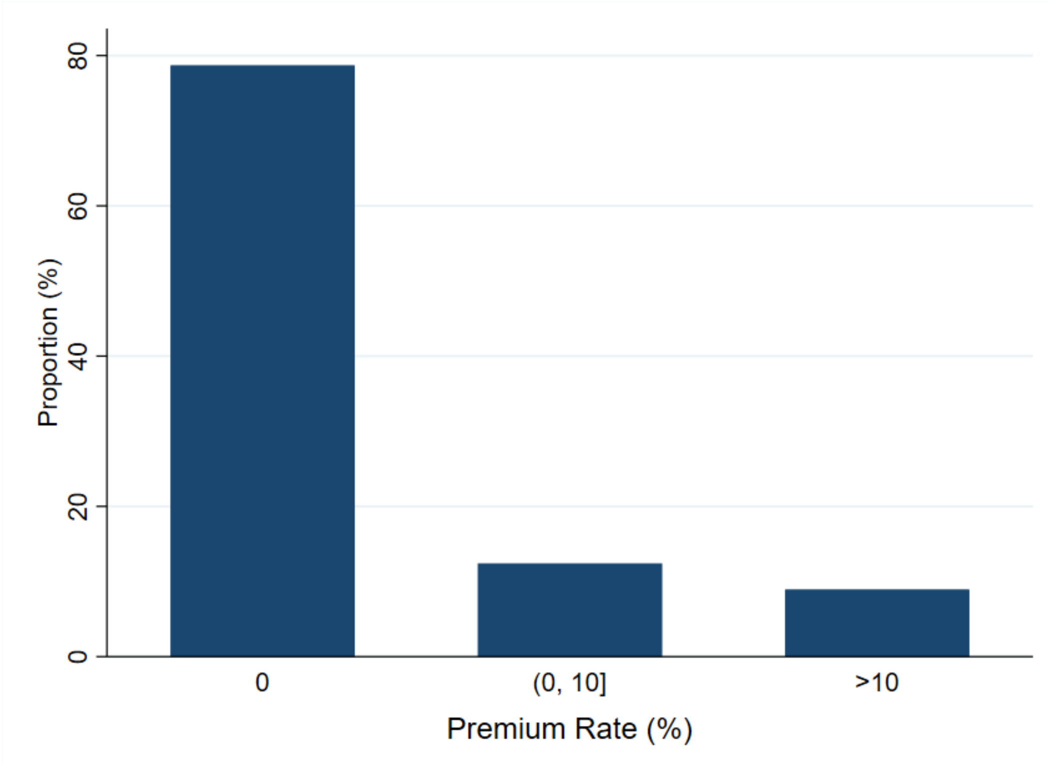


Figure A3: China's land auction: preminm above reserve prices, 2003–2017

Notes: The figure shows the proportion of land parcels that were sold at a premium above their reserve prices in China's primary land auctions. The left bar denotes the proportion of land parcels sold at a premium rate of 0%, transacted exactly at the reserve price. The middle bar shows the percentage of land parcels sold with a premium of no more than 10% above their reserve price. The right-side bar shows the proportion of land parcels sold with a premium rate over 10%.

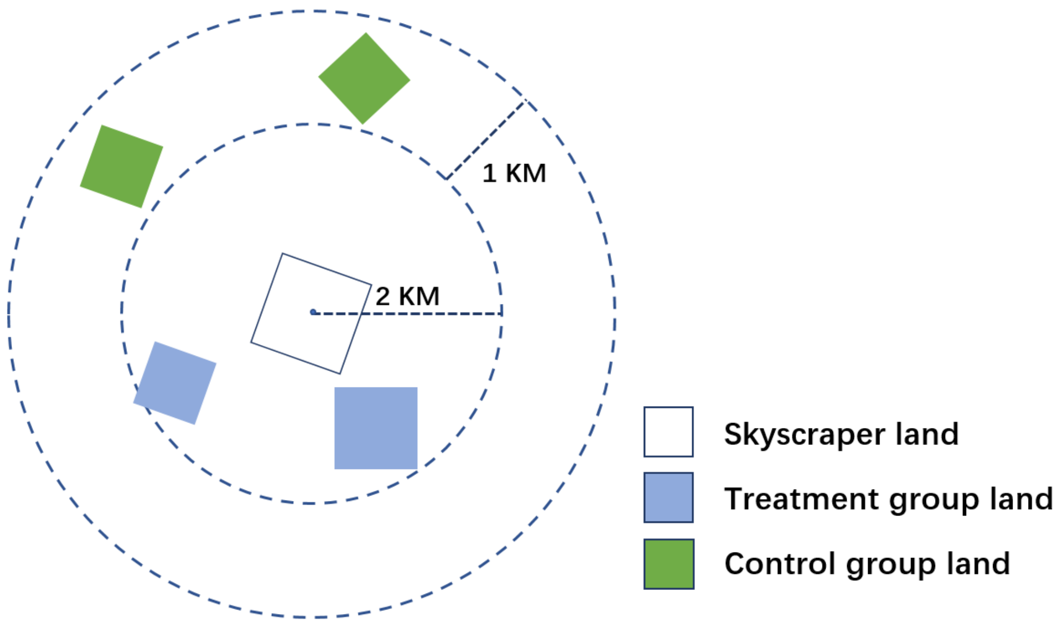


Figure A4: A Spatially Matched Sample for Identifying Spillovers

Notes: The figure illustrates the sample selection procedure for identifying a commercial skyscraper's spillover effects. Land parcels located within a 2km radius of a commercial skyscraper are selected as the treatment group (in blue). Those located within the 2–3km ring (in green) are selected as the control group. The commercial skyscraper land itself is excluded from the sample.

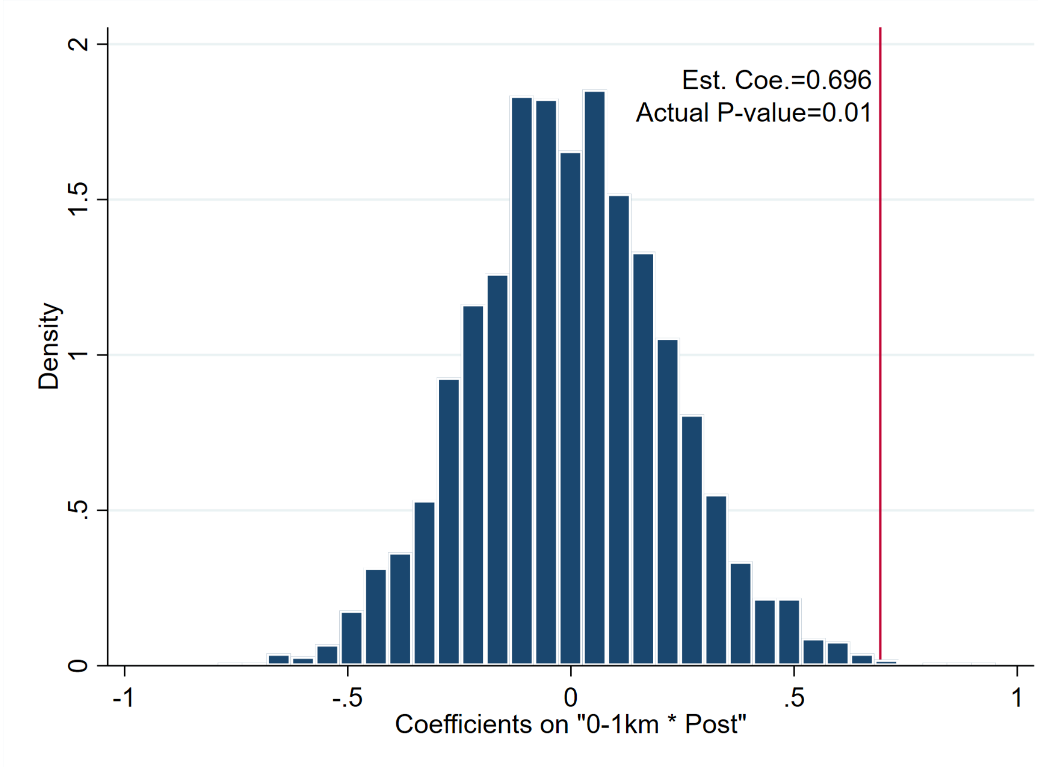


Figure A5: Spatial Randomization Test of Commercial Skyscraper Spillovers

Notes: The figure shows the distribution of the estimated coefficients from 2000 runs of a spatial randomization test, whereby the counterfactual locations were randomly chosen within 0–5km of the true skyscraper location. The red line is the baseline estimate (Column 3 of Table 4) and the p-value shows the likelihood of this estimate being drawn from the distribution.

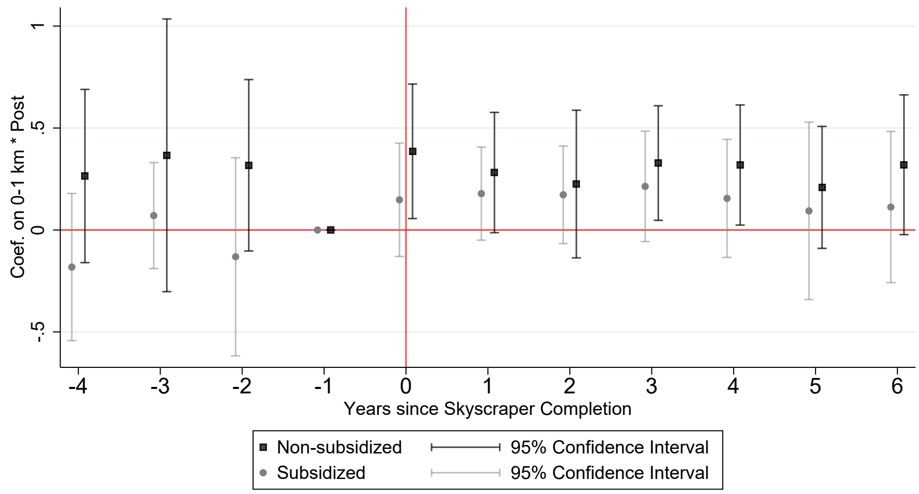


Figure A6: Event Study: Skyscrapers' Impacts on Nearby Public Land Supply

Notes: The figures plot the estimates on $\beta_{1,t}^{N}s$ for the 11-year event window based on Equation (6), where the dependent variable is the logarithm of the number of public land parcels supplied by the local government in concentric rings near commercial skyscrapers. Public land contains land parcels designated for the development of public transit, schools, cultural and sports facilities, and hospitals. The omitted category $t = -1$ is the year prior to the skyscraper's completion. The dynamic spillovers from unsubsidized (black squares) and subsidized (grey circles) commercial skyscrapers are separately reported. The effects on parcels sold more than 6 years after the skyscraper's completion are categorized into the event window "6 (plus)" and not reported, and those sold more than 4 years prior to completion are categorized into the event window "-4 (minus)" and not reported. The capped spikes (I-beams) plot the 95% confidence interval for the estimates.

Table A1: Distance Gradient: Intensive and Extensive Margins

	(1)	(2)	(3)
Panel A: Intensive Margin (Dep. Variable: Log Skyscraper Height)			
Log Euclidean Distance to CBD	0.0497		
	(0.0340)		
Log Euclidean Distance to CBD ***1**{Commercial Skyscraper}	-0.0922*		
	(0.0461)		
Log Distance to the Nearest Center		0.0498	
		(0.0340)	
Log Distance to the Nearest Center * **1**{Commercial Skyscraper}		-0.0961**	
		(0.0455)	
Log Road Network Distance to CBD			0.0402
			(0.0401)
Log Road Network Distance to CBD * **1**{Commercial Skyscraper}			-0.0804
			(0.0514)
Observations	545	545	545
Adjusted R^2	0.058	0.060	0.052
Panel B: Extensive Margin (Dep. Variable: Log # of Skyscrapers in 1km×1km Gridcell+1)			
Log Euclidean Distance to CBD	-0.163***		
	(0.0172)		
Log Euclidean Distance to CBD * **1**{Commercial Skyscraper}	0.125***		
	(0.0233)		
Log Distance to the Nearest Center		-0.151***	
		(0.0176)	
Log Distance to the Nearest Center * **1**{Commercial Skyscraper}		0.0956***	
		(0.0238)	
Log Road Network Distance to CBD			-0.177***
			(0.0189)
Log Road Network Distance to CBD * **1**{Commercial Skyscraper}			0.136***
			(0.0255)
Observations	8558	8558	8558
Adjusted R^2	0.222	0.221	0.222
Year FE	Yes	Yes	Yes

Notes:Panel A estimates the distance gradient at the intensive margin, by regressing the logarithm of skyscraper height on the logarithm of distance to the CBD and its interaction term with an indicator variable of skyscraper function (1 for commercial use, and 0 for residential use). Three measures of "distance to CBD" are used. Column 1 uses the Euclidean distance to the CBD, which is identified by the brightest 1km×1km grid-cell in each city's urbanized area (Baum-Snow et al., 2017; Tan et al., 2020). Column 2 considers polycentric urban structure and uses the Euclidean distance to the nearest center (including the CBD and sub-centers, where sub-centers are defined as cells whose pixel value exceeds 80% of the brightest cell's). Column 3 uses the actual travel distance to the CBD over the road network, which is calculated using the Open Source Routing Machine (OSRM) based on 2020 OpenStreetMap data (Huber and Rust, 2016). The sample is composed of 545 skyscrapers built between 2006 and 2014: 447 are commercial skyscrapers; the rest are residential skyscrapers. Panel B estimates the distance gradient at the extensive margin, by regressing the logarithm of (# of skyscrapers in 1km×1km grid–cell+1) on the logarithm of the three measures of distance to the CBD, respectively. The sample consists of 4279 1km×1km grid-cells that involved land transactions between 2003 and 2014. Matching the grids with the two types of skyscrapers doubles the number of observations to 8558. OLS regressions in all columns with year (skyscraper completion time) fixed effects included. Robust standard errors clustered at the province level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A2: Elasticity of Skyscraper Development with respect to Land Price: Intensive and Extensive Margins

	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
Panel A: Intensive Margin (Dep. Variable: Log Skyscraper Height)				
Log Predicted Land Value	0.103***	0.103***	0.256**	0.257**
	(0.0351)	(0.0358)	(0.121)	(0.122)
Log Predicted Land Value * **1**{Commercial Skyscraper}	-0.0689**	-0.0687**	-0.206*	-0.200*
	(0.0318)	(0.0342)	(0.113)	(0.113)
Observations	545	545	545	545
Adjusted R^2	0.180	0.174		
Weak Identification statistic			23.46	120.06
Panel B: Extensive Margin (Dep. Variable: Log # of Skyscrapers in 1km×1km Grid–cell+1)				
Log Predicted Land Value	0.0308***	0.0302***	0.0961***	0.132***
	(0.00165)	(0.00166)	(0.0104)	(0.0182)
Log Predicted Land Value * **1**{Commercial Skyscraper}	-0.0268***	-0.0268***	-0.0515***	-0.0514***
	(0.00227)	(0.00227)	(0.0128)	(0.0148)
Observations	8558	8558	8558	8558
Adjusted R^2	0.246	0.246		
Weak Identification statistic			38.8	13.5
Extra Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Instruments				
Distance to CBD	No	No	Yes	Yes
Distance to Public Park	No	No	Yes	Yes
Distance to Railway Station	No	No	Yes	Yes

Notes: Panel A estimates the response of skyscraper development with respect to land price at the intensive margin–the price–height elasticity, by regressing the logarithm of skyscraper height on the logarithm of the predicted skyscraper land value and its interaction term with an indicator variable of skyscraper function (1 for commercial use, and 0 for residential use). The sample is composed of 545 skyscrapers built between 2006 and 2014: 447 are commercial skyscrapers; the rest are residential skyscrapers.

Panel B estimates the response of skyscraper development with respect to land price at the extensive margin–the price–quantity elasticity, by regressing the logarithm of (the number of skyscrapers in 1km×1km grid–cell + 1) on the logarithm of the predicted skyscraper land value and its interaction term with an indicator variable of skyscraper function. The sample consists of 4279 1km×1km grid-cells that involved land transactions took place between 2003 and 2014. Matching the grids with the two types of skyscrapers doubles the number of observations to 8558. Columns 1–2 show the results of OLS regressions and columns 3-4 show the results of IV regressions with LIML. Extra controls include soil condition measured by city-level seismic precautionary intensity, the distance between the skyscraper and land parcels used in the skyscraper land value prediction, and the time difference between the skyscraper completion and the transaction time of land parcels used in the prediction. Year (skyscraper completion time) fixed effects are included in all columns. Standard errors in columns 1–2 are calculated on the basis of 1,000 bootstrap replications clustered at the province level. Robust standard errors clustered at the province level are reported in parentheses in columns 3–4 . Cragg-Donald Wald F statistics are reported for weak identification tests. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3: Land Price Elasticity of Height: U.S.

	Summary of estimated height–price elasticities (β_1^E)			
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
	0.202***	0.188***	0.102**	0.169***
Instruments				
Distance to CBD	No	Yes	No	Yes
Distance to Lake Michigan	No	Yes	No	Yes
Weak Identification Statistic	-	12.3	-	12.3
Observations	307	307	307	307
Adjusted R^2	0.46	-	0.46	-
Building type	Commercial	Commercial	Residential	Residential

Notes: This table reports the estimated land price elasticity of building height in 2010 from OLS and IV regressions in the U.S. (Chicago). The sample consists of 115 commercial skyscrapers and 192 residential skyscrapers over the 1980–2010 period. The instruments utilized are the logarithm of the distance from the CBD and the logarithm of the distance from Lake Michigan. Cragg-Donald Wald F statistics are reported for weak identification tests. Standard errors are clustered by skyscraper completion time cohorts (decades). Columns 1–2 reflect commercial skyscrapers. Columns 3–4 reflect residential skyscrapers. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A4: Policy Documents regarding Commercial Skyscraper Construction

City (1)	GDP Rank (2)	Land Discount (3)	Tax Reduction (4)	New Town (5)	Commercial Function (6)	Reference Number (7)
Shenzhen	3	✓	✓	✓		Shen[2005]41
Tianjin	5					Jin[2011]176
Nanjing	7	✓	✓	✓		Ning[2012]194
Hangzhou	11		✓	✓		Hang[2010]215
Qingdao	15		✓	✓	✓	Qing[2006]131
Zibo	29		✓	✓		Zi[2013]53
Nanning	44	✓	✓	✓		Nan[2011]19
Nantong	45	✓	✓	✓	✓	Tong[2006]41
Shijiazhuang	47		✓			Shi[2016]50
Yichang	63					Yi[2009]71
Yancheng	76		✓			Yan[2021]17
Baoji	81	✓	✓		✓	Bao[2007]19
Chifeng	94	✓	✓	✓		Chi[2007]221
Xinyu	101	✓				Yu[2009]5
Suqian	112	✓	✓			Su[2008]103
Huainan	115	✓	✓		✓	Huai[2013]12
Beihai	128					Bei[2011]1
Qinzhou	148	✓	✓			Qing[2013]41
Yangjiang	170		✓			Yang[2012]50
Yulin	180		✓		✓	Yu[2013]36
Baishan	182		✓			Bai[2008]12
Jiaozuo	186	✓	✓		✓	Jiao[2006]21
Loudi	189	✓	✓	✓		Lou[2008]5
Guigang	191	✓	✓		✓	Gui[2013]82
Laibin	213					Lai[2009]7
Baise	258	✓	✓			Bai[2017]36
Wenshan	267	✓				Wen[2019]15
Chongzuo	271		✓		✓	Chong[2021]3

Notes: This table shows a list of preferential policies implemented to support skyscraper development by 28 cities, ranked by their GDP in 2010 (column 2). Column 3 indicates whether the policy specifies details of skyscraper land discount terms and the conditions for obtaining them. Column 4 reports whether the policy includes tax reductions. Column 5 shows whether the policy provides support for commercial skyscrapers in new towns. Column 6 shows whether the policy restricts support to skyscrapers with a commercial function. Column 7 reports the reference number of the policy documents in each city.

Table A5: Average Land Price Discounts for Commercial Skyscrapers: Robustness Checks

	(1)	(2)	(3)	(4)
Commercial Skyscraper Land	-0.511***	-0.496***	-0.598***	-0.617***
	(0.133)	(0.137)	(0.154)	(0.171)
Matching radius	[$\leq 2km$]	[$\leq 1km$]]	[$\leq 2.5km$]	[$\leq 2.5km$]
Matched pair Obs.	[≥ 3]	[≥ 3]	[≥ 10]	[≥ 15]
Matched pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes
Spatial trend	Yes	Yes	Yes	Yes
Observations	2593	1299	2756	2518
Adjusted R^2	0.411	0.630	0.389	0.387

Notes: All columns use the specification in column 3 of Table 2, using the logarithm of the land transaction price as the dependent variable. Column 1 restricts the geo-matching radius to 2km. Column 2 further restricts the geo-matching radius to 1km. Column 3 requires the number of observations in each matched pair to be no fewer than 10. Column 4 requires the number of observations in each matched pair to be at least 15. The control variables include parcel characteristics such as the logarithm of the parcel size and its square, the transaction method, the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, access to public amenities, and a spatial trend. All regressions include matched pair and year fixed effects. Robust standard errors clustered at the matched pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A6: Predicted Promotion Likelihood of City Leaders

Dep. Variable	Dummy: Promotion of a city leader			
	Mayor (1)	Mayor (2)	Secretary (3)	Secretary (4)
Start age	-0.0213***	-0.0545***	-0.0227***	-0.0613***
	(0.00349)	(0.00924)	(0.00334)	(0.00915)
1{Deputy-province}	-1.475***	-4.001**	-0.629	-1.654
	(0.482)	(1.664)	(0.647)	(1.786)
1{Province or above}	-0.336	-0.648	-0.0935	0.219
	(0.921)	(2.675)	(0.549)	(1.795)
Start age * **1**{Deputy-province}	0.0254***	0.0684**	0.0119	0.0313
	(0.00934)	(0.0320)	(0.0130)	(0.0362)
Start age * **1**{Province or above}	0.00452	0.00690	0.00207	-0.00344
	(0.0176)	(0.0517)	(0.0101)	(0.0338)
1{Postgraduate degree}	-0.0423	-0.111	-0.0231	-0.0647
	(0.0320)	(0.0839)	(0.0322)	(0.0878)
Constant	1.494***	2.545***	1.507***	2.726***
	(0.169)	(0.446)	(0.171)	(0.463)
Summary statistics	Prediction of ex-ante likelihood of promotion			
1^{st} quartile	0.39	-0.28	0.30	-0.52
Median	0.45	-0.14	0.35	-0.40
3^{st} quartile	0.50	0.00036	0.42	-0.21
Model	Linear	Probit	Linear	Probit
Observations	1646	1646	1600	1600
Adjusted R^2	0.042		0.033	
Pseudo R^2		0.031		0.025

Notes: The table reports the predicted *ex ante* likelihood of mayor and secretaries' promotions from a linear probability model and probit regressions. The sample covered 1646 mayors and 1600 secretaries who were in office between 2003 and 2015, sourced from Jiang (2018). Following Wang et al. (2020), we regress the promotion dummy on the leader's start age (age at their appointment), the dummies of start levels (province or above and deputy province, with prefecture omitted as a reference category), the interactions of start age and dummies for the start levels, and a dummy indicator of the leader's educational attainment (whether or not they hold a postgraduate degree). These parameter estimates are used to predict the ex-ante promotion likelihood for each mayor and secretary, and the prediction results are summarized and reported in the middle panel. Standard errors in parentheses are clustered at the city level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A7: Alternative Explanations: Supply-Side Confounding Factors

Dep. Variables	Parcel Size	Distance to CBD	Land Evaluation	English Auction	Two-stage Auction	Transaction Volume
	(1)	(2)	(3)	(4)	(5)	(6)
0-1 km * Post	-0.0947	-0.0383	0.455	-0.0527	0.0527	0.00732
	(0.296)	(0.0689)	(0.445)	(0.0585)	(0.0585)	(0.128)
1-2 km * Post	0.212	0.0560	-0.371	-0.0368	0.0368	0.231*
	(0.244)	(0.0793)	(0.304)	(0.0669)	(0.0669)	(0.128)
Control group	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]	[3-4km]
Skyscraper matched sample–year FE	Yes	Yes	Yes	Yes	Yes	Yes
Skyscraper matched sample–ring FE	Yes	Yes	Yes	Yes	Yes	Yes
Other parcel characteristics	Yes	Yes	Yes	Yes	Yes	No
Spatial trend	Yes	Yes	Yes	Yes	Yes	No
Observations	3004	3004	3004	3004	3004	728
Adjusted R^2	0.589	0.922	0.825	0.721	0.721	0.757

Notes: Columns 1–5 show spatial DID analysis at the land parcel level, using Equation (3). The dependent variables in columns 1–5 are parcel characteristics (parcel size, distance to CBD, land evaluation grade, transaction method (an English auction dummy), and transaction method (a two-stage auction dummy), which are proxies for the quality of the supplied land. Column 6 shows spatial DID analysis at the ring level, using the variant of Equation (6). The dependent variable in column 6 is the volume of land transactions, which is aggregated at the ring-by-year level. Land parcel characteristics (the logarithm of parcel size and its square, the transaction method, the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, and access to public amenities) and a spatial trend other than the one used as the dependent variable, are controlled in columns 1–5. All regressions include skyscraper matched sample–year and skyscraper matched sample–ring fixed effects. Standard errors are clustered at the skyscraper level and reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A8: Heterogeneous Land Price Discounts to Commercial Skyscrapers in Ill Locations

Dep. Variable	Log Land Transaction Price		
	(1)	(2)	(3)
Commercial Skyscraper Land	-0.512***	-1.067***	-0.955***
	(0.125)	(0.181)	(0.278)
Commercial Skyscraper Land * **1**{Tier 1/2 City}		0.631***	
		(0.224)	
Commercial Skyscraper Land * **1**{CBD}			0.688**
			(0.295)
Matching radius	[$\leq 2.5km$]	[$\leq 2.5km$]	[$\leq 2.5km$]
Matched pair Observations	[≥ 3]	[≥ 3]	[≥ 3]
Matched pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes
Spatial trend	Yes	Yes	Yes
Observations	3147	3147	3147
Adjusted R^2	0.405	0.405	0.407

Notes: Using a spatially matched sample within a 2.5km radius of the skyscraper, column 1 repeats the baseline estimates of column 3 in Table 2 for reference. Column 2 includes an interaction term between the commercial skyscraper land dummy and a city size measure that equals 1 if the skyscraper city is categorized as tier 1 or tier 2 (Glaeser et al., 2017). Column 3 interacts the skyscraper land dummy with the skyscraper's within-city location (a dummy that is equal to 1 if the skyscraper was built in the CBD). The control variables include parcel characteristics such as the logarithm of the parcel size and its square, the transaction method, the land evaluation grade, the floor area ratio, the logarithm of the distance to the CBD, access to public amenities, and a spatial trend, all as previously defined. All regressions include matched-pair and year fixed effects. Robust standard errors clustered at the matched pair level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A9: City-wide Impacts of Commercial Skyscrapers

Dep. Variable	Log Land Price in the CBD				Log (# of Firms+1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (# of Commercial Skyscrapers+1)	0.00631	0.0530			0.0425	0.0281		
	(0.0986)	(0.106)			(0.0353)	(0.0304)		
1{Skyscraper city}			0.0195	-0.020			0.0390	0.001
			(0.134)	(0.029)			(0.0332)	(0.002)
Method	TWFE	TWFE	TWFE	Wald-DID	TWFE	TWFE	TWFE	Wald-DID
City FE	Yes	Yes	Yes	-	Yes	Yes	Yes	-
Time FE	Yes	Yes	Yes	-	Yes	Yes	Yes	-
City controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	489	468	468	348	792	763	763	552
Adjusted R^2	0.582	0.586	0.586	-	0.988	0.989	0.989	-

Notes: This table reports the estimated city-wide impacts of commercial skyscrapers, using Equation (8). Columns 1–4 use the logarithm of land price in the CBD as the dependent variable. Following the lead of Albouy et al. (2018), we estimate the land price in the CBD to ensure the measure is comparable across time and regions. Specifically, we perform a loop for each city, and regress the logarithm of land transaction prices on the logarithm of the parcel's distance to the CBD and other parcel characteristics (the logarithm of parcel size and its square, transaction method, land evaluation grade, floor area ratio, and access to public amenities), obtaining the estimated intercept term which represents the land price in the CBD. Columns 5–8 use the logarithm of the number of new firms as the dependent variable. Skyscraper city is a dummy variable that equals 1 if the city has built a commercial skyscraper, and otherwise 0. Columns 1–3 and 6–8 use a two-way fixed effect (TWFE) model. To mitigate concerns about heterogeneous treatment effects due to the staggered roll-out of commercial skyscrapers, columns 4 and 8 present the alternative Wald-DID estimators (De Chaisemartin and d'Haultfoeuille, 2020). Cities that had commercial skyscrapers before 2003 are excluded from our sample, and cities that built their first commercial skyscraper after 2015 are selected as the control group. City-level controls include the logarithm of city employment, the share of residents with university degrees, and road density. All regressions include city and year fixed effects. Robust standard errors clustered at the city level are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.