Government–Directed Urban Growth, Firm Entry, and Industrial Land Prices in Chinese Cities

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Abstract

We examine the effects of a large-scale administrative reorganization in China, where counties are annexed into cities to accommodate urban spatial expansion. We present a simple model to illustrate how this government-directed urban growth via annexation may affect firm entry decisions and in turn land market outcomes. The key idea is that annexation indicates the direction of future urban expansion and helps coordinate expectation. Using nationwide data on land-lease transactions, we find that annexation raises industrial land prices in the annexed counties by 7 percent but does not reduce land prices in neighboring counties and central cities. We show that the annexed counties experienced increases in firm entry and investment, offering a plausible mechanism for the effect on industrial land prices.

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1 Introduction

Coordination failures among land developers and local governments can distort the spatial allocation of economic activity and reduce overall urban productivity. In cities with multiple jurisdictions, the decentralized provision of public goods often results in both overinvestment and underinvestment in infrastructure across different areas (Bordeu 2025). Large exogenous shocks—such as urban fires that destroy significant portions of a city—can create rare opportunities for coordinated redevelopment, thereby mitigating these failures (Siodla 2015, Hornbeck and Keniston 2017). In other cases, governments can take an active role in fostering coordination by providing credible development commitments, as demonstrated in the revitalization of cities like Detroit (Owens et al. 2020).

An important yet underexplored mechanism through which governments coordinate expectations and reduce uncertainty in urban development is administrative reclassification, particularly the annexation of peripheral areas into central cities. This strategy has been widely employed in rapidly urbanizing developing countries such as China (Zhang and Wu 2006), Vietnam (Leducq and Scarwell 2018) and India (Jha 2022), as well as in developed nations including Denmark (Allers and Geertsema 2016), Germany (Blesse and Baskaran 2016), Israel (Reingewertz 2012), Japan (Li and Takeuchi 2023), and the United States (Austin 1999). While urban planning theory recognizes the importance of government-led coordination, the directive role of governments in shaping urban growth through administrative reclassification remains insufficiently examined in the urban economics literature.

This study examines how "government directed urban growth" (henceforth DUG)—specifically, the annexation of surrounding counties into central cities—affects urban land markets in China. China provides a compelling context for two reasons. First, since 2010, Chinese governments have frequently reclassified adjacent administrative units—typically autonomous county-level jurisdictions—as parts of central cities, thereby bringing them under the authority of prefectural-level governments. This nationwide policy shift offers a unique opportunity to study annexation as a form of DUG. Second, China publicly discloses parcel-level land transaction data—a rarity globally and a significant advantage for empirical analysis. A persistent challenge in studying urban growth and sprawl is the lack of high-resolution geographic data (Patacchini and Zenou 2009). China's detailed land market data enable us to evaluate how this DUG policy through annexation influenced industrial land prices in the affected areas. Moreover, unlike short-term indicators such as GDP or population, land prices are forward-looking and reflect expectations about future local economic development. As such, they are particularly well-suited to capture the long-term effects of government-directed urban growth.

We motivate our empirical analysis by a model of firm investment under uncertainty, adapting the framework of Brueckner and Picard (2015). In this model, a firm considers an irreversible investment in one of two counties, a and b, and faces the choice of investing immediately or waiting. The initial (period 1) returns—differing between the two counties—are known, but second-period returns are stochastic, and an unfavorable realization may reverse the initial ranking of the two counties. Therefore, the firm may delay investment until period 2 to observe these uncertain outcomes and make a better-informed location decision. The trade-off involves comparing the foregone return from delaying investment with the option value of waiting.

Theoretically, DUG that annexes a nearby county into the central city affects firm investment decisions in two key ways. First, annexation likely increases the initial return to investing in the annexed county, making it more attractive for immediate entry. Second, it reduces uncertainty about future returns in the annexed county, thereby lowering the option value of waiting. Together, these effects make immediate investment in the annexed county more appealing. As more firms enter, competition for land intensifies, putting upward pressure on industrial land values and driving up prices in the annexed county.

Our primary data source is administrative land transaction records released by China's Ministry of Natural Resources, which provide detailed information on individual land parcels. We supplement this information with data from the Ministry of Civil Affairs on the reclassification of surrounding counties into urban districts. These two datasets are merged based on parcel location. Using this merged data, we construct a panel of land transactions that includes: (1) treated counties reclassified as urban districts, (2) existing urban districts, and (3) neighboring counties that remained unchanged during the sample period and serve as controls. The combination of parcel location and transaction date allows us to identify whether a given transaction occurred in a newly reclassified urban district.

We use the difference-in-differences (DID) approach to estimate the effect of DUG via annexation on industrial land prices. Annexation raises industrial land prices in treated counties by about 7 percent. This effect is robust to alternative heterogeneity-robust estimators and further controlling for initial county-level characteristics. Moreover, we find no significant impact on industrial land prices in existing urban districts and their neighboring non-annexed counties, suggesting that the estimated price effect is not driven by spillover effects.

We further investigate the mechanisms underlying the observed price effects by examining firm entry and investment activity in annexed counties. Our results show that annexation—by integrating a county into the central city—encourages firms to establish operations and expand investment in the affected areas. These patterns suggest that annexation raises the expected profitability of doing business in annexed counties, potentially due to anticipated infrastructure improvements, population growth, or reduced uncertainty. As a result, competition for industrial land intensifies, driving up land prices.

In addition, we investigate how annexation's land-price effects vary with the initial characteristics of the central city, including GDP, the number of industrial enterprises, population size, and population density. The results show that annexation raises land prices only when the central city is already relatively well developed.

This study is closely related to the extensive literature on urban spatial growth, or sprawl, which highlights four main drivers of urban expansion. The first and most prominent is economic factors, such as population growth, rising incomes, and lower commuting costs, whose effects are often amplified by market failures, including the undervaluation of open-space amenities and the unpriced social costs of congestion (Brueckner and Fansler 1983, Brueckner 2000, Irwin and Bockstael 2004, McGrath 2005, Song and Zenou 2006, Anas and Rhee 2006, Baum-Snow 2007, Brueckner 2007, Anas and Pines 2008, Deng et al. 2008, Paulsen 2012, Coisnon et al. 2014). Second, local geography, including terrain ruggedness, ground water availability, and urban shape, also plays a role (Burchfield et al. 2006, Harari 2020). Third, political-economy factors such as jurisdictional fragmentation (Mills et al. 2006, Ehrlich et al. 2018) and the growth incentives faced by local politicians (Lichtenberg and Ding 2009, Solé-Ollé and Viladecans-Marsal 2013, Wang et al. 2020) further influence patterns of expansion. Finally, policies such as urban growth boundaries and land use regulations are key institutional drivers (Bento et al. 2006, Cunningham 2007, Anas and Rhee 2007, Brueckner and Sridhar 2012, Dempsey and Plantinga 2013).

Our paper adds to this literature by focusing on government-directed growth, distinct from previous studies aimed at correcting externalities or curbing sprawl. Thus, we offer a new perspective on the role of government in shaping urban growth.

Our paper also contributes to a growing literature on jurisdictional adjustments, which investigates the determinants of such adjustments and their regional economic impacts. Hanes et al. (2012) finds that income and size differences of the municipalities in Sweden affect their willingness to amalgamate. Wu and Chen (2015) propose a model showing that cities in regions with lower agricultural land rents, construction costs, and income growth uncertainty tend to spread out more and consist of more municipalities. Regarding regional impacts, Austin (1999) shows that annexation can offset the political effects of income and racial shifts. Previous studies also highlight economies of scale in public service provision as a key rationale for municipal consolidation (Tyrefors Hinnerich 2009, Reingewertz 2012, Allers and Geertsema 2016, Blesse and Baskaran 2016, Hirota and Yunoue 2017). In China, Tang and Hewings (2017), Liu et al. (2019), and Han and Wu (2024) documented annexation's growth-promoting effect; Xiao et al. (2023) and Bo and Wang (2025) showed an income-enhancing effect, while Deng et al. (2022) found that annexation reduced per capita GDP in surrounding rural areas.[1] Our paper adds to this literature by linking annexation to parcel-level land prices, capturing both immediate and forward-looking effects in a developing country with rapid urban expansion.

In addition, our study contributes to a growing literature on urban land markets in China, which explores various topics including corruption in land markets (Cai et al. 2013, Chen and Kung 2019, Li 2019), the impact of floor-area-ratio restrictions (Brueckner et al. 2017, Cai et al. 2017), the effects of land quotas (Fu et al. 2021, Qin et al. 2016), and the role of reservation land prices (Lin et al. 2020). It also explores the impact of industrial land markets on local development (He et al. 2022, Tian et al. 2022, 2023). We contribute to this strand of literature by quantifying the effects of a different policy practice, DUG via annexation, on land markets and investigating the underlying mechanism.

The paper is organized as follows. Section 2 discusses the institutional background. Section 3 presents a simple model to motivate empirical analysis. Section 4 introduces the data and reports some descriptive evidence. Section 5 presents the empirical framework.

[1] A small literature in Chinese explored annexation's effects on expanded central cities. See, for example, Tang and Wang (2015), Shao et al. (2018), Zhang et al. (2018), Zhuang et al. (2020), Jin et al. (2021), and Zhang et al. (2022). We learned a great deal of background information from this literature.

Sections 6 and 7 report the empirical results. Finally, we conclude in Section 8.

2 Government-directed urban growth in China

Government-directed urban growth through the annexation of surrounding counties has been the dominant mode of urban spatial growth in China over the past two decades.[2] To annex a county into a prefecture's central city, the prefectural government needs to first ensure the county's consent and submit a plan to the provincial government for approval. Upon approval, the plan is forwarded to the State Council for final ratification, following a formal review process. In the early 2000s, China launched the first wave of administrative restructuring, promoting the reclassification of counties into municipal districts to expand central cities.[3] However, due to immature land markets and limited transaction data at that time, it is difficult to evaluate the effects of this early wave on urban land markets.

A renewed effort to expand central cities began in the past decade, particularly after the launch of the *National New Urbanization Plan* in 2014.[4] Figure A.1 shows the annual number of counties reclassified as municipal districts from 2010 to 2019. By 2019, 135 counties had been reclassified, 97 of which are included in our sample.[5] As depicted in Figure 1, these sample counties/districts are geographically dispersed across China.

[Insert Figure 1 here]

Despite the scale of annexation, there are no formal, publicly stated criteria for approval. Unofficial sources suggest that approvals are more likely for prefectures with strategic importance in the provincial urban system, favorable geographic conditions, and strong growth potential. The prefecture's central city is typically required to have a sizable economy, high population density, and relatively advanced development level. Candidate counties are expected to exhibit high urbanization, strong secondary and tertiary sectors, developed infrastructure, and well established social security system.[6]

[2]Appendix A introduces the administrative system in China. See Mutreja et al. (2021) and Shifa and Xiao (2023) for more details.

[3]Earlier cases of county-to-district conversion (*che xian she qu* in Chinese) occurred sporadically but not at scale.

[4]See `http://www.gov.cn/gongbao/content/2014/content_2644805.htm` for the *National New Urbanization Plan (2014-2020)*.

[5]Some counties are excluded for comparability; see the data section for details.

[6]In 2014, the Ministry of Civil Affairs circulated a draft guideline proposing that eligible counties have an urbanization rate above 50%, a GDP with at least 80% from the second and tertiary industries,

The annexation-driven urban growth has several salient features (illustrated in Figure A.2 in the Online Appendix). First, prefectures with multiple peripheral counties can choose among them when expanding their central city. Second, annexation typically involves reclassifying the entire county as a new district without changing jurisdictional boundaries. In rare cases, only part of a county is annexed, typically with special purposes such as establishing an Economic Development Zone. These exceptions are excluded from our analysis due to their limited number. Third, newly annexed districts always border the original city core; remote counties are not considered. Finally, central cities prior to annexation were typically small and compact, indicating a need for spatial expansion.

Naturally, annexation entails more than a change in jurisdiction—it triggers a broader process of administrative and functional integration. The new district is required to contribute a larger share of its revenue to the prefecture government, which in turn invests in upgrading infrastructure and expanding public transit to integrate the new district into the broader commuting zone. Policies on education, healthcare, social security, and civil services are aligned to treat residents of annexed counties as regular urban citizens (Zhuang et al. 2020). By placing previously separate jurisdictions under a unified authority, annexation also fosters greater coordination across urban districts (Tang and Wang 2015, Zhang et al. 2018).

3 Model

3.1 Basic analysis

The analysis explores how DUG annexing a county into the central city affects firm investment decisions and in turn industrial land prices. The analytical framework is adapted from the option model proposed by Brueckner and Picard (2015).[7]

Imagine a typical metropolitan area in China, where rapid urban expansion creates uncertainty for manufacturing firms' locational choices due to shifting land use plans and unpredictable infrastructure investments. Frequent zoning adjustments make it difficult

and adequate public infrastructure and social security systems meeting specified standards. However, this draft was never formally adopted and subsequent practices clearly diverged from these guidelines. For details, see: `http://jx.sina.com.cn/news/b/2015-08-06/detail-ifxftkpe2756185-p2.shtml`.

[7] While their model portrays government infrastructure investment under uncertainty rather than the investment decision of a private firm, the setup is easily adapted to this choice. Beyond the option model, which is used here, their paper also includes an alternative "signaling" model of the investment choice.

for firms to anticipate whether an area will remain viable for industrial use. Large-scale infrastructure projects, such as highways and logistics hubs, significantly impact production and distribution costs, yet their timing and placement are often uncertain. As a result, manufacturing firms may delay investment or adopt flexible strategies to hedge against unexpected changes.

The regional economy in the current model has two counties, denoted a and b, which are both adjacent to a central city considering annexation. The model also has two time periods, denoted 1 and 2.[8] A firm must decide in which of the two counties to make a single, irreversible investment and whether the investment should be made in period 1 or 2. The investment requires a one-time outlay of c on physical capital, which is combined with one unit of land to produce output. For the moment, we ignore the firm's payment for land, which is to be determined by the firm's pre-rent profit.

The initial (period-1) return from the investment in county b equals θ, while the initial return in county a equals $\theta + \delta$ where $\theta > 0$ but δ could be either positive or negative, indicating that the period-1 return can be higher or lower in county a than in county b. However, $\theta + \delta > 0$ holds, so that county-a return is positive. The future is uncertain, with returns in period 2 equal to $(\theta + \delta)\epsilon_a$ in county a and $\theta\epsilon_b$ in county b, where ϵ_a and ϵ_b are positive random variables. Given this uncertainty, the firm may wish to delay its investment until period 2, at which point the realizations of ϵ_a and ϵ_b are known, and the county with the highest return going forward can be chosen. If the firm instead decides to invest in period 1, however, it will choose county a if $\delta > 0$ and county b otherwise.

The goal of the analysis is to investigate how annexation of county a by the central city affects the firm's investment decision. We assume that annexation raises δ, increasing the firm's return in county a relative to that in county b, a change that could be driven by new infrastructure investment in the annexed county. In addition, we assume that annexation reduces period-2 uncertainty in the annexed county, making the variance of ϵ_a smaller. With county a more closely tied to the fortunes of the central city following annexation, future economic conditions become less uncertain. After further analysis setting up the firm's choice problem, we show that both these changes make the firm more likely to make its investment in county a, the annexed county, in period 1. Therefore, annexation

[8]While period 2 could be viewed as composite of all future periods beyond period 1, as in Brueckner and Picard (2015), assuming instead that it has the same length as period 1 simplifies the treatment of discounting and the resulting notational burden.

hastens investment and directs it toward the annexed county.

Assuming for simplicity that ϵ_a and ϵ_b have the same expected value, equal to μ, the expected net returns from investing in counties a and b in period 1 are, respectively, equal to

$$R_{1a} \;=\; \theta \,+\, \delta \,-\, c \,+\, \rho(\theta+\delta)\mu, \qquad R_{1b} \;=\; \theta \,-\, c \,+\, \rho\theta\mu, \tag{1}$$

where $\rho < 1$ is the discount factor. From (1), it is clear that, if the firm invests in period 1, then it chooses county a (county b) as $\delta > (<)\ 0$. With annexation raising δ, let us assume that, whatever δ's initial sign, its post-annexation value is positive. Thus, if county a has a pre-annexation return disadvantage relative to county b, annexation reverses it, while if it has a pre-annexation return advantage, annexation strengthens it. The upshot is that, if the firm invests in period 1, annexation leads it to choose county a.

However, by waiting to invest and thus observing the realizations of the random variables, the firm can choose the higher of the post-period-1 net returns, which may occur in county b. Accordingly, the expected net return from waiting until period 2 to invest is given by

$$R_2 \;=\; \rho\ Emax\{(\theta+\delta)\epsilon_a - c,\ \theta\epsilon_b - c\}. \tag{2}$$

Note that the period-1 return is absent.

With annexation implying that investment in period 1 (if it happens) occurs in county a, waiting to invest is not optimal when $R_{1a} > R_2$, or when

$$\theta \,+\, \delta \,-\, c \,+\, \rho(\theta+\delta)\mu \;>\; \rho\, E\, max\{(\theta+\delta)\epsilon_a - c,\ \theta\epsilon_b - c\}. \tag{3}$$

Rearranging (3) after extracting c from the expected value, the condition becomes

$$\theta \,+\, \delta \,-\, (1-\rho)c \;>\; \rho\, E\, max\{(\theta+\delta)\epsilon_a,\ \theta\epsilon_b\} \;-\; \rho(\theta+\delta)\mu. \tag{4}$$

The RHS of (4) gives the option value of waiting to invest. This value equals the expected discounted period-2 net return from putting the investment in the best county (the first term), measured relative to the expected discounted period-2 net return from investing in county a in period 1, given by $\rho(\theta+\delta)\mu$. Since the LHS of (4) represents the loss of net return associated with waiting to invest, satisfaction of (4) indicates that this loss exceeds the option value of waiting, so that waiting is not optimal.[9]

Note that the option value in (4) differs from that in a standard option framework because it captures the firm's ability to choose between *two* investment locations once future conditions become clear. In the usual option model, by contrast, waiting gives the investor a choice between investing or not investing once the future is revealed. Here, the choice is between two alternate investment locations under the assumption that investing somewhere is always optimal.[10]

To rewrite the RHS of (4) in a more usable form, observe that the first term inside the max expression in (4) is optimal (so that county a receives the investment in period 2) when $\epsilon_a > g\epsilon_b$, where $g = \theta/(\theta+\delta)$ captures the relative loss from investing in county b. Conversely, county b receives the investment when $\epsilon_a < g\epsilon_b$.

Let $t(\epsilon_a, \epsilon_b)$ denote the joint density of ϵ_a and ϵ_b, and suppose that both random variables have support $[\underline{\epsilon}, \overline{\epsilon}]$, with $\overline{\epsilon} > \underline{\epsilon} > 0$. Then

$$\rho\, E \max\{(\theta{+}\delta)\epsilon_a,\ \theta\epsilon_b\} \;=\; \rho \int_{\epsilon_b=\underline{\epsilon}}^{\overline{\epsilon}} \left[\int_{\epsilon_a=g\epsilon_b}^{\overline{\epsilon}} (\theta+\delta)\epsilon_a t(\epsilon_a,\epsilon_b) d\epsilon_a \;+\; \int_{\epsilon_a=\underline{\epsilon}}^{g\epsilon_b} \theta\epsilon_b t(\epsilon_a,\epsilon_b) d\epsilon_a \right] d\epsilon_b. \tag{5}$$

Note that $\epsilon_a > g\epsilon_b$ holds over the range of integration of the first integral inside the brackets in (4), with $\epsilon_a < g\epsilon_b$ holding over the range of the second integral.

With further manipulation, the condition (4) for the non-optimality of waiting reduces to[11]

$$\theta \;+\; \delta \;-\; (1-\rho)c \;>\; \rho(\theta+\delta) \int_{\epsilon_b=\underline{\epsilon}}^{\overline{\epsilon}} \int_{\epsilon_a=\underline{\epsilon}}^{g\epsilon_b} (g\epsilon_b - \epsilon_a) t(\epsilon_a,\epsilon_b) d\epsilon_a d\epsilon_b. \tag{6}$$

[9] The period-1 return of $\theta+\delta$ is lost via waiting. To understand the $(1-\rho)c$ term in (4), note that since ρ is the factor for discounting period 2 income back to period 1, it embodies a discount rate r satisfying $\rho = 1/(1+r)$, so that $(1-\rho)c = rc/(1+r)$. This expression equals the period-1 present value of the interest earned in period 2 on a bank deposit of c made in period 1 as an alternative to making the investment, which is gained when the investment occurs in period 2. Subtracting this gain from the $\theta+\delta$ loss due to waiting, the LHS of (4) equals the (net) loss from waiting to invest.

[10] To ensure that the option of not investing at all is unattractive, a sufficiently low value of c is assumed.

[11] Observe that the second term on the RHS of (4) can be written as

$$\rho(\theta+\delta)\mu \;=\; \rho(\theta+\delta) \int_{\epsilon_b=\underline{\epsilon}}^{\overline{\epsilon}} \int_{\epsilon_a=\underline{\epsilon}}^{\overline{\epsilon}} \epsilon_a t(\epsilon_a,\epsilon_b) d\epsilon_a d\epsilon_b.$$

Subtracting this expression from (5), RHS of (4) can then be rewritten as

$$\rho \int_{\epsilon_b=\underline{\epsilon}}^{\overline{\epsilon}} \left[\int_{\epsilon_a=\underline{\epsilon}}^{g\epsilon_b} -(\theta+\delta)\epsilon_a t(\epsilon_a,\epsilon_b) d\epsilon_a \;+\; \int_{\epsilon_a=\underline{\epsilon}}^{g\epsilon_b} \theta\epsilon_b t(\epsilon_a,\epsilon_b) d\epsilon_a \right] d\epsilon_b.$$

To simplify this expression, $\theta+\delta$ is factored out (recall $g = \theta/(\theta+\delta)$), and the resulting expression is then substituted in place of the RHS of (4), yielding (6).

Again, this condition says that the loss from waiting to invest exceeds the option value of waiting.

3.2 Full comparative-static effects of annexation

While we have already seen that the higher δ due to annexation makes county a, the annexed county, the preferred location for a period-1 investment by the firm, inspection of (6) yields a number of additional comparative-static predictions about the timing of investment. First, since $\rho < 1$, an increase in c reduces the LHS of (6) and thus favors waiting to invest, reflecting gains from delaying the investment cost. The same conclusion applies to an increase in ρ. However, a higher θ raises both the new LHS of (6) and the new RHS (via a higher g), so that an increase in this parameter, which shifts the returns in both counties, has an ambiguous effect on waiting decision.

More importantly, after dividing (6) by $\theta + \delta$, it can be seen that an increase in δ, the post-annexation return advantage in county a, raises the new LHS and reduces the new RHS (since g falls), changes that make waiting to invest less desirable. The intuition is that a higher δ raises the period-1 return that is lost by waiting. Therefore, the higher δ associated with annexation not only makes county a the best place for a period-1 investment, but it also reduces the attractiveness of waiting. Therefore, the possibility that the firm invests in period 2, possibly doing so in county b, is reduced. The higher δ from annexation thus pulls the firm's investment toward period 1, where it will be made in the annexed county.

As noted above, a second expected effect of annexation would be reduction in uncertainty regarding the business climate in county a, given that the county is now part of an annexing central city. In the context of the model, a reduction in uncertainty in county a would reduce the variance of the random variable ϵ_a that affects the county's period-2 returns, without affecting uncertainty in county b.

It is unfortunately not possible, using (6), to derive analytically the effect of such a reduction in uncertainty. However, the effect can be illustrated in numerical examples. In particular, under the assumption that the random terms ϵ_a and ϵ_b have a bivariate normal distribution, the effect of a decrease in ϵ_a's standard deviation, denoted σ_a, on the option value of waiting (magnitude of the RHS of (6)) can be assessed numerically. Based on a number of different parameterizations of the bivariate normal, results show that the

RHS of (6) decreases in magnitude when σ_a decreases, moving away from equal degrees of uncertainty. With the option value of waiting then falling, the waiting decision becomes less desirable when uncertainty in county a declines, an intuitively sensible result given that, with less future uncertainty in that county, a firm is less likely to regret a decision to invest in period 1.

[Insert Table 1 here]

For the calculations, the common mean of ϵ_a and ϵ_b is set at 3.0, and the standard deviation σ_b of ϵ_b is set at 1.0. With σ_a (the standard deviation of ϵ_a) varying from from 1.0 to 0.2 and the large means of ϵ_a and ϵ_b, the probability of negative values of these random variables is virtually zero, as assumed. Finally, $g = \theta/(\theta + \delta)$ is set at 0.7. Table 1 shows the magnitude of the option value as σ_a falls from 1.0 to 0.2 under several values of the correlation coefficient of ϵ_a and ϵ_b, denoted $\sigma_{a,b}$ (it equals 0.6, 0.4, and 0.2). As can be seen, the option value falls monotonically in each column of Table 1, except at the bottoms of columns (1) and (2), where it increases slightly as σ_a falls. This pattern, where the option value rises slightly with σ_a when the standard deviation is small, appears in some other parameterizations as well. But for all parameterizations, the option value is decreasing in σ_a as it initially falls below σ_b, indicating that a reduction in uncertainty in county a, starting from a position of equality, reduces the option value of waiting.

This effect, along with the annexation's effect on δ, makes a firm more likely to invest immediately (choosing county a) after the county's annexation. Thus, the assumed effects of county a's annexation on the firm's (expected) return in the county (the positive effect on δ) and on the period-2 uncertainty of the county-a return (the negative effect on σ_a) both reduce the option value of waiting, pulling the firm's investment toward period 1, where annexation makes county a the preferred choice.

Another noteworthy feature of Table 1 is that option value increases as the covariance $\sigma_{a,b}$ falls, moving horizontally across Table 1. When this covariance is high, as in the first column, there is little chance that county a's initial advantage will be reversed in period 1, leading to a low option value of waiting. On the other hand, when the covariance is low, the chance of a reversal is greater, making the option value higher.

3.3 Effects on land prices

To link annexation to land prices, consider that a firm must acquire a unit of land to invest, a standard assumption that does not alter the foregoing analysis. Under competition, firms bid up the land price until the discounted net return equals the land cost, driving economic profit to zero. The resulting land price, which captures the firm's willingness-to-pay for land, then equals the relevant net return expression from above. In other words, the (county a) land price paid by a firm investing in period 1 equals $p_{a,1} = (1 + \rho\mu)(\theta + \delta) - c$ after rearranging (1) (recall that μ is the common mean of ϵ_a and ϵ_b). Since $p_{a,1}$ increases with δ, annexation raises a firm's willingness-to-pay (hence its "demand") for land in county a in period 1, when its post-annexation investment is made, which in turn raises the land price. The model then predicts that annexation should immediately (in period 1) raise industrial land prices in the annexed county.

The price increase is driven by new firm entry or additional investment by existing firms. Firms that invested before annexation paid a lower land price based on the original value of δ. After annexation, as δ rises, the discounted return net of land cost would become positive, attracting new entrants. Competition among firms would bid up the land price until profits are again driven to zero. Therefore, firm entry in county a and the rising land price occur simultaneously.

One caveat to these predictions concerns land supply. In China, urban land is state-owned and effectively controlled by the prefecture government. If the government aims to maximize land revenue, it should allocate land to any firm offering more than the land's agricultural value, and the model's predictions should hold. However, if the government prioritizes farmland preservation or faces strict land conversion quotas (Fu et al. 2021), then it may restrict industrial land supply. In such cases, firm entry and investment may not increase substantially. Nonetheless, even without actual transactions, competition among *potential* entrants would still bid up land prices following annexation.

Given that the model's most robust prediction is a rise in industrial land prices following annexation, we will devote the bulk of our empirical analysis below to this hypothesis. We will also examine whether annexation leads to increases in firm entry and investment.

4 Data and descriptive statistics

4.1 Data

This study draws on three primary data sources. First, we collect information of administrative division adjustments from the Ministry of Civil Affairs of China, identifying all instances in which counties were reclassified as municipal districts.[12] For each case, we record the year of annexation and create a dummy variable, DUG, equal to 1 if the annexation has occurred. We also identify the central city involved and all counties adjacent to it but not annexed. Land price and other outcome variables are collected for annexed counties (treated group), the corresponding central cities, and adjacent but not annexed counties (control group).

Second, we obtain parcel-level land transaction data from the website of *landchina*, maintained by the Ministry of Natural Resources, which provides detailed land use information since 2007.[13] Each record includes leasehold length, land grade, redevelopment status (newly converted or redeveloped land), buyer's industry code, transaction mode (e.g., auction, transfer by agreement, government appropriation), and the level of approval authority (local or higher-level government). We compute the price per hectare using transaction price and area, deflated to the 2010 price level using provincial CPI. As county-to-district reclassification was suspended for a few years before 2010 and high-quality land transaction data were unavailable before 2007, we restrict our analysis sample to transactions from 2010 onward.

Third, we use regional statistics from yearbooks, including GDP, population, population density, fixed-asset investments, and local government finance. The yearly number of new firms in counties and municipal districts is calculated using enterprise registration data from the State Administration for Market Regulation. To assess a county's relative position within a prefecture, we calculate the distance between the county's geographic centroid and that of the prefecture.

We apply several data trimming procedures. First, we use county IDs to restrict land parcels to those located within the sample counties and municipal districts. Second, we keep land transactions from 2010 to 2019. Third, we retain only parcels designated for industrial uses, including manufacturing, mining, water supply, and storage. Fourth,

[12]See `http://www.mca.gov.cn/article/fw/cxfw/jzz/`.

[13]The *landchina* website is `https://www.landchina.com`.

we exclude transactions with missing prices or areas. Fifth, to ensure comparability across provinces, we drop counties from the four centrally administered municipalities (Beijing, Chongqing, Shanghai, and Tianjin), as well as from Xinjiang and Tibet, due to their distinct geographic, administrative, cultural, and policy contexts. The final sample comprises 97 treated counties annexed to central cities from 2010–2019, and 155 control counties adjacent to but not annexed by central cities, covering over 56,000 industrial land transactions during the sample period.

4.2 Descriptive statistics

Table 2 presents descriptive statistics for county-level economic indicators in the initial sample year (2010). Column (1) reports data for treated counties, Column (2) for control counties, and Column (3) shows differences between the two groups, controlling for province fixed effects. p-values are reported in parentheses in Column (3). There are no statistically significant differences in total population or rural population between treated and control counties. Similarly, GDP and value added in the secondary and tertiary sectors do not differ significantly at conventional levels. To assess a county's relative importance within its prefecture, we use two indicators: GDP share and financial revenue share. Neither shows a significant difference, suggesting that treated and control counties were similarly important within their respective prefectures. Lastly, healthcare provision—measured by hospital beds per capita—also shows no significant difference. Overall, Table 2 suggests that treated and control counties were statistically similar across key economic and demographic dimensions at the beginning of the sample period.

[**Insert Table 2 here**]

One might naturally expect more developed counties to be more likely candidates for annexation, making the lack of significant differences in Table 2 somewhat surprising. However, it is important to recognize that while counties located near a central city are generally more developed than remote ones, counties within this adjacent group tend to be relatively similar to one another. This is precisely why we use neighboring counties as the control group. The patterns in Table 2 also reflect an institutional constraint: significantly more developed counties may resist annexation. Since the policy requires agreement from the county to be annexed, and annexation entails a substantial loss of administrative autonomy, county leaders—especially in economically stronger areas—may have little incentive to support such a move. A widely reported case involves *Changxing* county in Zhejiang Province. In 2013, there was a proposal to annex it into the city of *Huzhou*, which was later blocked by hundreds of county cadres in anticipation of diminished administrative authority (Zhang et al. 2018). In any case, this observed comparability between treated and control counties supports the use of a simple and transparent empirical strategy to evaluate the effects of annexation.

5 Empirical strategies

We use a difference-in-differences (DID) approach to examine the impact of annexation on industrial land prices.[14] Counties adjacent to central cities that were not annexed and reclassified as municipal districts during the sample period serve as the control group. Specifically, we estimate the following regression:

$$\log Price_{icpt} = \alpha + \beta * DUG_{icpt} + \psi * X_{icpt} + f_c + \delta_{pt} + \varepsilon_{icpt}, \tag{7}$$

where $\log Price_{icpt}$ denotes the logarithm of industrial land price per hectare for parcel i in county or district c, province p, and year t. The key explanatory variable, DUG_{icpt}, is a dummy equal to 1 if county c had been annexed and reclassified as a municipal district in year t or earlier, and 0 otherwise. The coefficient β captures the causal effect of annexation on industrial land prices. X_{icp} denotes all control variables, f_c is a county fixed effect, and δ_{pt} is a province-by-year fixed effect.

X_{icpt} includes a set of land parcel characteristics: dummies for transaction mode,

[14] We explored several alternative strategies (see Online Appendix G for details). We tried three alternative control groups in the DID estimations. The first group consists of counties that applied for annexation but were not approved. This specification yields slightly smaller estimates than our baseline, but the control group fails the balance test. The second group consists of matched counties identified through a PSM procedure, and the resulting estimates are almost identical to our baseline. The third group is a synthetic control in a synthetic DID method implemented at the county level, which also yields results consistent with our baseline. We also explored an instrumental variables (IV) approach. Using a LASSO procedure to identify predictors of annexation, we found that the county seat's distance to the city center was the strongest predictor. Using this as an instrument, our IV estimates similarly show a significant effect of annexation. However, the IV strategy relies on the exclusion restriction that distance affects land price growth only through its impact on annexation, a strong assumption we are unwilling to make. We therefore do not adopt the IV strategy as our baseline. Finally, following a referee's suggestion, we examined whether annexation decisions were based on a threshold rule (e.g., a minimum share of non-agricultural GDP) that might justify an RD design. We systematically tested for such thresholds but found none.

land grade, parcel area, leasehold length, the level of the approving government, and distance to the county center. To control for time-varying price trends within counties, we include interactions between year dummies and each county's median land price in 2010, allowing for flexible county-specific time trends. Standard errors are clustered at the county/district level to account for within-county correlation in the error terms (Moulton 1986, Bertrand et al. 2004).

As shown in Figure 1, our sample includes counties and districts across China, which exhibit significant variation in economic development. Time-invariant county-level characteristics—such as proximity to economic centers, land abundance, and industrial infrastructure—can influence local industrial land markets. For example, counties closer to national or regional hubs may attract more firms and have higher land prices, while land-rich counties may experience lower prices due to greater supply. To account for such differences, we include county fixed effects (f_c) in the regression and focus on within-county variation over time.

During our sample period (2010–2019), China experienced a series of domestic and international shocks. For example, the central government repeatedly called on provincial authorities to strengthen land market regulation. Since the 18th National Congress of the CPC in 2012, poverty alleviation policies targeting underdeveloped rural counties may have affected industrial land markets differently across more and less developed regions. International events—most notably the escalating U.S.-China trade tensions—also influenced industrial activity and land demand. Given China's vast regional diversity, the impacts of these shocks likely varied across provinces and over time. To account for this possibility, we include province-by-year fixed effects (δ_{pt}) in the regression.

In addition to estimating the average effects, we also examine the dynamic impacts of annexation by using the following flexible specification:

$$\log Price_{icpt} = \alpha + \sum_{j=-5}^{-2} \beta_j * before_{icpj} + \sum_{j=0}^{4} \beta_j * after_{icpj} + \psi * X_{icpt} + f_c + \delta_{pt} + \varepsilon_{icpt}. \quad (8)$$

The key explanatory variables are $before_{icpj}$ and $after_{icpj}$, which are dummy variables indicating the year of the transaction relative to the year in which county c was annexed and converted into a municipal district. The year immediately preceding the annexation ($j = -1$) is omitted and serves as the reference category.

6 Empirical results

6.1 Baseline results

6.1.1 Average effects of the annexation

Table 3 presents the estimated effects of DUG via annexation on industrial land prices, based on Equation (7). Column (1), which controls for land price trends, county fixed effects, and province-year fixed effects, shows that annexation of an adjacent county into a central city increases industrial land prices in the treated county by 8.42 percent. Column (2) adds controls for land-parcel characteristics, including parcel area, leasehold length, land grade, transaction mode, whether the parcel is newly converted for urban use, the level of the approving government, and distance to the county center. It shows a somewhat smaller but still significant increase of 6.96 percent.

[Insert Table 3 here]

6.1.2 Dynamic effects of annexation

[Insert Figure 2 here]

To investigate the year-by-year effects of annexation, we estimate Equation (8) using the same set of controls as in Column (2) of Table 3. Figure 2 plots the coefficients of the year-distance indicators, using the year prior to annexation as the reference. The dots represent the estimated coefficients, and the vertical lines denote the 95 percent confidence intervals. For $j < -1$, the coefficients are not significantly different from zero, suggesting that the parallel trends assumption holds. In contrast, for $j > 0$, the coefficients become significantly positive, indicating that annexation led to higher industrial land prices. These year-by-year estimates from the flexible specification thus reinforce the baseline finding that annexation significantly increased industrial land prices in the treated counties.[15]

[15] We also estimate Equation (7) using only the sample of annexed counties, comparing industrial land prices before and after annexation. The results are consistent with the baseline DID estimates (see Online Appendix C).

6.1.3 Robustness checks

We conduct two sets of robustness checks to strengthen the validity of our baseline results. First, a key concern is omitted variable bias stemming from unobserved initial county characteristics that may influence both the likelihood of annexation and the trajectory of industrial land prices. To address this possibility, we control for each county's 2010 characteristics—population, GDP, industrial structure (share of the secondary sector in GDP), and urbanization rate—interacted with year dummies in the specification of Equation (7). The results remain consistent with our baseline estimates (see Table A.2 in Online Appendix D). Second, to account for potential bias from staggered treatment timing, as highlighted in recent studies (Cengiz et al. 2019, de Chaisemartin and D'Haultfœuille 2020, Callaway and Sant'Anna 2021, Goodman-Bacon 2021, Sun and Abraham 2021, Gardner et al. 2024), we apply five heterogeneity-robust DID estimators (see Online Appendix E for details). As shown in Figure 3, these results align closely with those in Figure 2, indicating parallel pre-trends and a positive treatment effect.[16]

[Insert Figure 3 here]

6.2 Further analysis

6.2.1 Impacts on neighboring regions

One potential concern is that the rise in land prices in treated counties may have come at the expense of price declines in neighboring areas. To assess this possibility, we examine the impact of annexation on industrial land prices in both central cities and adjacent counties within the control group. Columns (1) and (2) of Table 4 report the coefficients on the DUG dummy, estimated by comparing land prices before and after annexation in central cities and in neighboring counties that were not annexed, respectively. These are regular regressions that do not use a DID specification. In both cases, the coefficients are small in magnitude and statistically insignificant, indicating that annexation had no significant impact on industrial land prices in surrounding regions. This suggests that the observed increase in land prices within treated counties is unlikely to have been driven by a redistribution of economic activity from other areas within the same prefecture.

[16] We also conducted two placebo tests by randomly assigning annexation timing and status. The results suggest that the estimated effects of annexation on land prices are unlikely to be driven by unobserved confounding factors (see Online Appendix F).

Instead, it is more likely the result of increased entry driven by the reduced option value of waiting, as suggested by our theoretical model.

[Insert Table 4 here]

6.2.2 Heterogeneity by characteristics of central cities

The impact of annexation may depend on the characteristics of the central city. For instance, the estimated average price-enhancing effect of annexation may arise only in prefectures where the central city has high economic output or population density. In contrast, in prefectures with weaker central cities, urban growth through annexation may have little or no effect on land prices. To examine how the effect of annexation varies with central city characteristics, we estimate the following equation:

$$\log Price_{icpt} = \alpha + \beta * DUG_{icpt} + \gamma * DUG_{icpt} * CityChar_{2010} + \psi * X_{icpt} + f_c + \delta_{pt} + \varepsilon_{icpt}, \quad (9)$$

where $CityChar_{2010}$ represents characteristics of the central city in 2010, the first year of our sample. Specifically, we consider four central city attributes: GDP, the number of industrial enterprises, population density, and total population.

[Insert Figure 4 here]

We conduct the heterogeneity analysis in two steps. First, we estimate equation (9) using our baseline DID strategy. Second, using the estimated coefficients, we calculate the marginal effect of annexation based on the central city's ranking for each of the four characteristics. Panel A of Figure 4 illustrates the marginal effect of annexation (i.e., $\hat{\beta} + \hat{\gamma} * CityChar_{2010}$) when the central city's GDP is at the 5th, 25th, 50th, 75th, and 95th percentiles. The horizontal axis represents the marginal effect on industrial land prices; the left vertical axis shows the GDP percentile rank, while the right vertical axis reports the corresponding GDP values. Dots represent the calculated marginal effects; horizontal lines denote 95 percent confidence intervals. As shown in Panel A, annexing a peripheral county into the central city significantly increases land prices only when the central city ranks above the 50th percentile in GDP. Below that threshold, the effect is statistically indistinguishable from zero. This pattern suggests that a sufficiently large economic base is a precondition for annexation to affect land prices.

Panel B ranks all central cities by the number of industrial enterprises. Here too, annexation boosts industrial land prices only when the central city has a large number of enterprises in the initial period. Panel C ranks central cities by population density and shows that only those at or above the 50th percentile experience significant increases in industrial land prices. Panel D, which ranks central cities by total population, yields a similar pattern: annexation significantly raises land prices only when the central city is at or above the 75th percentile.

In sum, the effect of government-directed urban growth through annexation appears conditional on the strength of the central city. Specifically, annexation significantly raises industrial land prices in treated counties only when the central city is already relatively well developed.

7 Analysis of firm entry and investment

As shown above, our model also predicts that DUG via annexation should raise firm entry and investment in annexed counties. In this section, we test this prediction by examining the effect of annexation on both outcomes. The firm entry analysis covers the period 2010–2019, consistent with the land price analysis. For investment, due to data limitations, the sample ends in 2017.

[**Insert Table 5 here**]

Table 5 reports the estimated effects of annexation based on specification (7). Using the log number of new firm entries as the dependent variable, Column (1) shows that annexation increases firm entry by 6.22 percent.[17] Column (2), which uses the log of total investment in fixed assets at the county level as the dependent variable, finds that annexation raises investment by approximately 10 percent.

These findings support the theoretical mechanism proposed earlier: annexation stimulates land demand by promoting firm entry and investment, leading to increases in land prices. By directing the expansion of central cities toward annexed counties, governments effectively identified likely areas for future city growth, reducing the incentive to postpone investment in these areas. As economic activity rises, so do expected returns and firms' willingness to pay for land, which in turn intensifies competition and drives up land prices.[18]

[17] See Online Appendix H for a visualization of this effect.

[18] One may suspect that government land supply behavior could affect industrial land prices. However,

8 Conclusion

Urban growth or sprawl driven by market forces has been widely studied and critiqued in the U.S. and European contexts (Brueckner 2000, Patacchini and Zenou 2009). In contrast, empirical evidence on the effects of government-directed urban expansion remains scarce. Leveraging a large-scale administrative reorganization in Chinese cities and detailed data on land-lease transactions, this paper examines the impact of such directed expansion on industrial land prices and new firm entry in annexed areas.

Our results show that when a central city annexes an adjacent county, industrial land prices in the annexed area rise by approximately 7 percent. The price effect is more pronounced when the central city has a larger economy or greater economic or population density. These gains appear to reflect improvements in local economic vitality, evidenced by increased firm entry and greater investment in fixed assets, both of which contribute to upward pressure on land prices.

The richness of our land transaction dataset enables us to evaluate directed urban growth (DUG) in China—an urban expansion policy widely practiced but largely understudied. We believe our findings offer a comprehensive view of how such policies influence industrial development in a large, rapidly urbanizing economy.

Despite this progress, important questions remain. In particular, what mechanisms drive firm entry in annexed counties? Our theoretical model highlights the roles of improved infrastructure and reduced uncertainty following annexation. We interpret annexation as an implicit "development guarantee" by the government (see Owens et al. (2020)). However, alternative explanations are plausible. Entrepreneurs might anticipate enhanced agglomeration economies due to more coordinated urban and industrial planning, or an expanded labor pool as annexed counties become more attractive to migrants. Disentangling these channels empirically represents a promising direction for future research.

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our ancillary analysis finds no evidence of a decrease in industrial land supply or a drastic increase in the use of auctions (see Online Appendix I). We also conducted a parallel analysis to examine the impact of annexation on residential and commercial land prices (see Online Appendix J).

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Tables and Figures

Table 1: Dependence of option value on county a's standard deviation

	(1)	(2)	(3)
σ_a	$\sigma_{a,b} = 0.6$	$\sigma_{a,b}= 0.4$	$\sigma_{a,b} = 0.2$
1.0	0.0536	0.0911	0.1280
0.9	0.0397	0.0731	0.1068
0.8	0.0289	0.0578	0.0879
0.7	0.0211	0.0454	0.0715
0.6	0.0160	0.0359	0.0578
0.5	0.0134	0.0291	0.0470
0.4	0.0128	0.0251	0.0389
0.3	0.0142	0.0234	0.0336
0.2	0.0169	0.0241	0.0309

Notes: Table 1 shows the magnitude of the option value as σ_a falls from 1.0 to 0.2 under several values of the correlation coefficient of ϵ_a and ϵ_b, denoted $\sigma_{a,b}$ (it equals 0.6, 0.4, and 0.2). For the calculations, the common mean of ϵ_a and ϵ_b is set at 3.0, and the standard deviation σ_b of ϵ_b is set at 1.0. With σ_a (the standard deviation of ϵ_a) varying from from 1.0 to 0.2 and the large means of ϵ_a and ϵ_b, the probability of negative values of these random variables is virtually zero, as assumed. Finally, $g = \theta/(\theta + \delta)$ is set at 0.7.

Table 2: Characteristics of counties in 2010

Variable	(1) Treatment group	(2) Control group	(3) Difference
Population (100,000)	57.742	60.626	-4.667
	(28.593)	(34.348)	(0.197)
Rural population (100,000)	48.629	50.755	-3.782
	(24.833)	(30.200)	(0.245)
GDP (million yuan)	189.683	168.538	5.345
	(176.692)	(234.527)	(0.834)
Secondary sector GDP (million yuan)	105.800	91.749	3.878
	(106.171)	(148.099)	(0.809)
Tertiary sector GDP (million yuan)	60.054	54.436	0.364
	(64.918)	(84.908)	(0.969)
Ratio of county to central-city GDP (%)	11.800	10.578	0.275
	(10.429)	(13.705)	(0.853)
Ratio of county to central-city revenue (%)	29.049	26.005	3.787
	(35.647)	(36.584)	(0.404)
Debt to GDP ratio	0.507	0.509	-0.014
	(0.282)	(0.270)	(0.602)
Number of students (100,000)	0.712	0.736	-0.077
	(0.453)	(0.478)	(0.145)
Hospital beds per 10000 people	25.048	25.273	1.154
	(10.737)	(12.782)	(0.422)
Observations	97	155	252

Notes: Column (1) reports the summary statistics of county-level characteristics in 2010 for counties treated by the annexation. Column (2) reports the summary statistics of county-level characteristics in 2010 for counties that are adjacent to the central city but were not annexed by the central city during the sample period (2010–2019). In Columns (1)-(2), standard deviations are in parentheses. Column (3) reports the differences conditional on province fixed effects and p-values are reported in parentheses.

Table 3: Baseline DID results

DV: Log industrial land price	(1)	(2)
DUG	0.0842***	0.0696***
	(0.0298)	(0.0267)
Parcel-level controls	No	Yes
Price_trend	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	56620	56620
Adjusted R^2	0.690	0.730

Notes: This table reports the results of the DID estimation in which the control group is treated counties' neighboring counties that are adjacent to the central city. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Price trend is controlled by the interaction terms between year dummies and the county's median land price in 2010. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effects of annexation in the central city and neighboring counties

DV: Log industrial land price	(1) Central city	(2) Neighboring counties
DUG	0.0093	-0.0183
	(0.0419)	(0.0325)
Parcel-level controls	Yes	Yes
Price_trend	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	34999	32664
Adjusted R^2	0.403	0.746

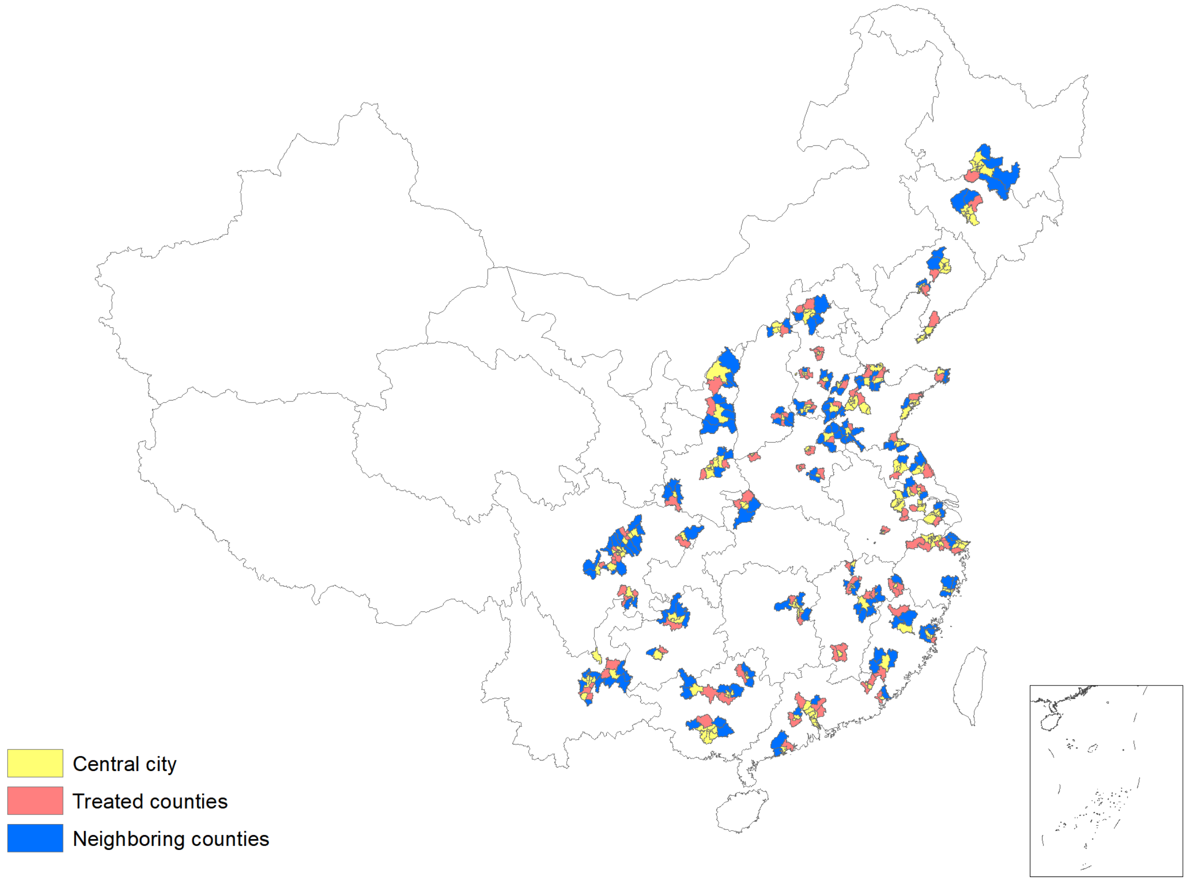
Notes: This table reports the effects of annexation on industrial land prices in central cities and neighboring counties that are adjacent to the central city but have not been annexed by the central city during the sample period (2010–2019). Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Price trend is controlled by the interaction terms between year dummies and the central city's or county's median land price in 2010. Standard errors are clustered at the central city level in Column (1) and at the county level in Column (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of annexation on new enterprises and investment in fixed assets

	(1) DV: Log no. of newly registered enterprises	(2) DV: Log investment
DUG	0.0622*	0.1006***
	(0.0326)	(0.0387)
Controls	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	2280	1908
Adjusted R^2	0.944	0.936

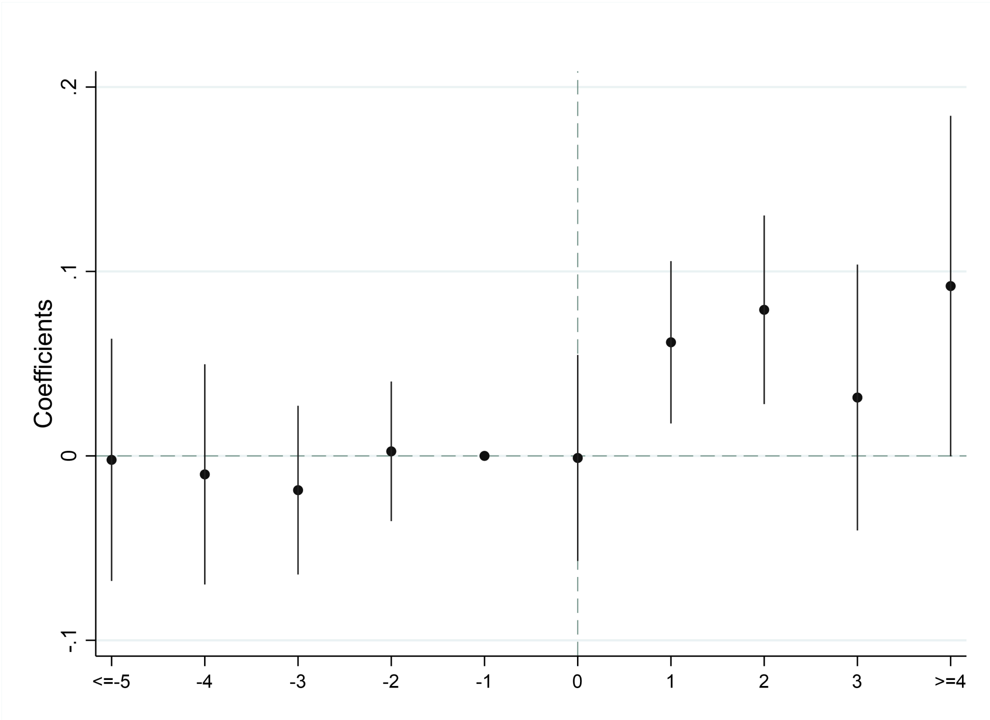
Notes: Column (1) reports the effect of annexation on the number of newly registered enterprises from 2010 to 2019. Column (2) reports the effect of annexation on investment in fixed assets from 2010 to 2017. These are DID estimations in which the control group is neighboring counties that are adjacent to the central city but were not annexed by the central city during the sample period. Controls include the following 2010 county/district characteristics: log population, log GDP, share of second-sector GDP in total GDP, and urbanization rate. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Central cities, annexed counties, and neighboring counties in the sample



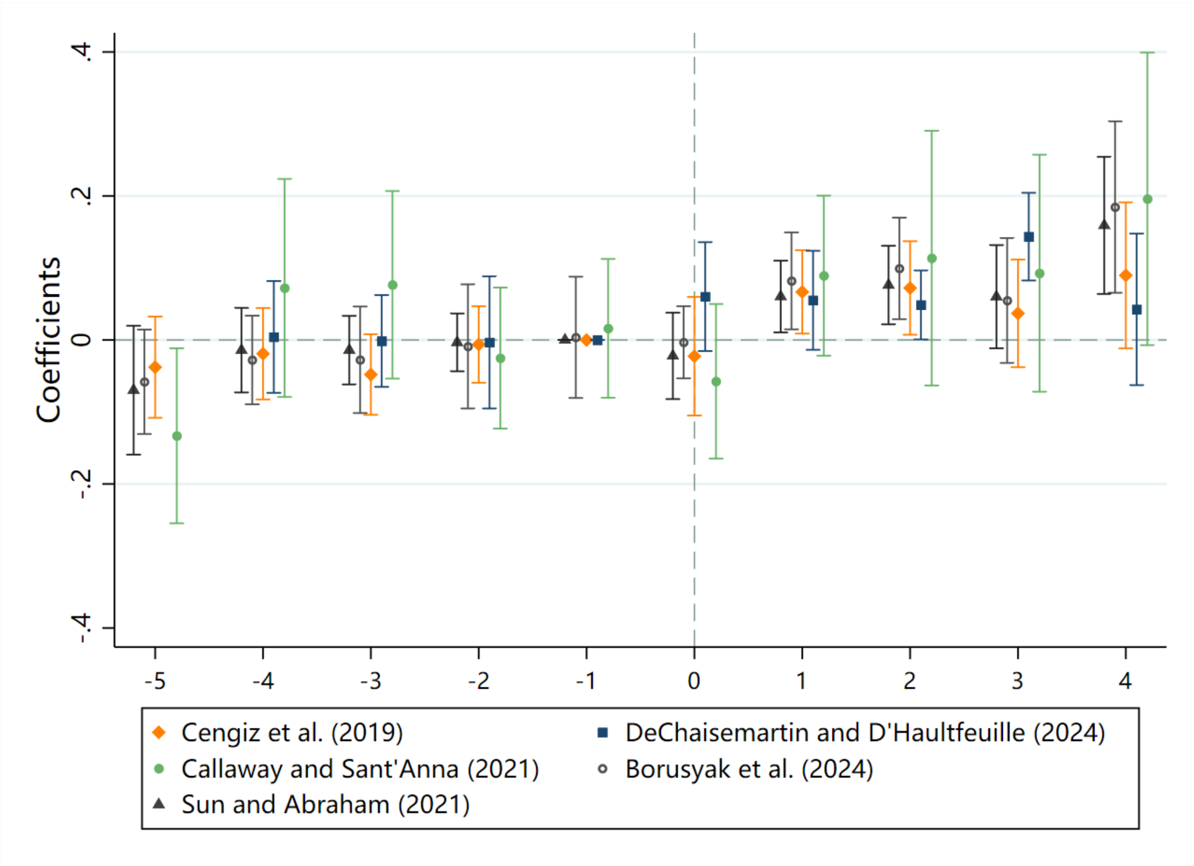
Notes: Figure 1 shows city annexations in China during our sample period (2010–2019). Annexations in Xinjiang, Tibet, and the four province-level direct-control municipalities (Beijing, Chongqing, Shanghai, and Tianjin) are not included in the data. The yellow areas represent the central city in 2010, the red areas represent the annexed counties during the sample period (2010–2019), and the blue areas represent the counties that are adjacent to the central city but have not been annexed into the central city.

Figure 2: Dynamic effects of annexation



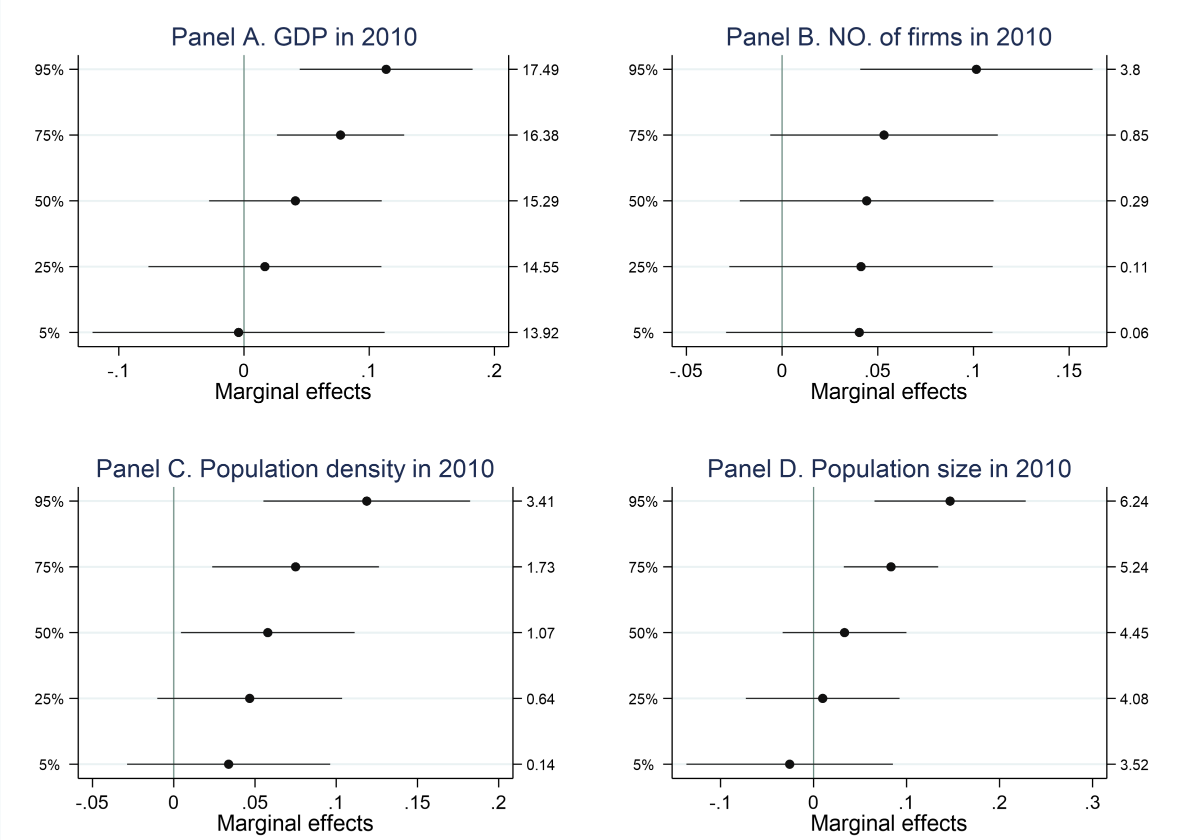
Notes: This figure plots the DID coefficients of year distance indicators estimated from Equation (8), using one year prior to annexation as the reference year. Control variables included are the same as those in Table 3 (see notes under the table). The dots represent the values of estimated coefficients, and the vertical lines represent the 95 percent confidence intervals.

Figure 3: Dynamic treatment effects: alternative estimators



Notes: Results from five heterogeneity-robust DID estimators are presented in this figure. The first one follows the approach used by, among others, Cengiz et al. (2019). Specifically, we first divide treated counties in our sample into different groups based on the treatment year; for each group, we use the never-treated adjacent counties as the control group. We then run a stacked regression with separate fixed effects for each group of treated units and their controls. The next three methods, instead of estimating the effects from the stacked data, estimate cohort-specific effects first and then aggregate them up, with Sun and Abraham (2021) and Callaway and Sant'Anna (2021) using each cohort's relative frequencies as weights to compute a weighted average and de Chaisemartin and D'Haultfœuille (2024) computing a simple average. The final estimator applies the imputation method by Borusyak et al. (2024). A two-way fixed-effects model of land prices (as specified in Equation (8)) is first fitted using untreated counties' data. This model is then used to predict counterfactual land prices for treated counties. The difference between actual and counterfactual prices provides the estimated treatment effect.

Figure 4: Effects of annexation and characteristics of the central city



Notes: From the estimated Equation (9), these marginal effects for each city characteristic are calculated as $\hat{\beta}+\hat{\gamma}*CityChar_{2010}$ at different percentiles of the city characteristic. The horizontal axis represents the marginal effect of the annexation on industrial land prices; the left and right vertical axes represent the ranking and value of the central city's characteristics inlcuding GDP (Panel A), the number of industrial enterprises (Panel B), population density (Panel C), and population (Panel D); the dots represent the calculated marginal effects; and the horizontal lines represent the 95 percent confidence intervals.

Online Appendix – Not For Publication

A. Administrative classifications in China

Mainland China has a five-tier government structure: national, provincial (including provinces, autonomous regions, and centrally administered municipalities), prefectural, county/district, and township levels. On average, a province has 11 prefectures, and a typical prefecture consists of a central city—comprising one or more municipal districts—and a surrounding peripheral region made up of several counties. In response to rapid population and economic growth in central cities over recent decades, many prefectures have expanded their urban cores by annexing adjacent counties. By 2019, the final year of our sample, China had 333 prefectures, 965 municipal districts, and 1,881 counties. The average prefecture contained 2.9 districts and 5.65 rural counties.

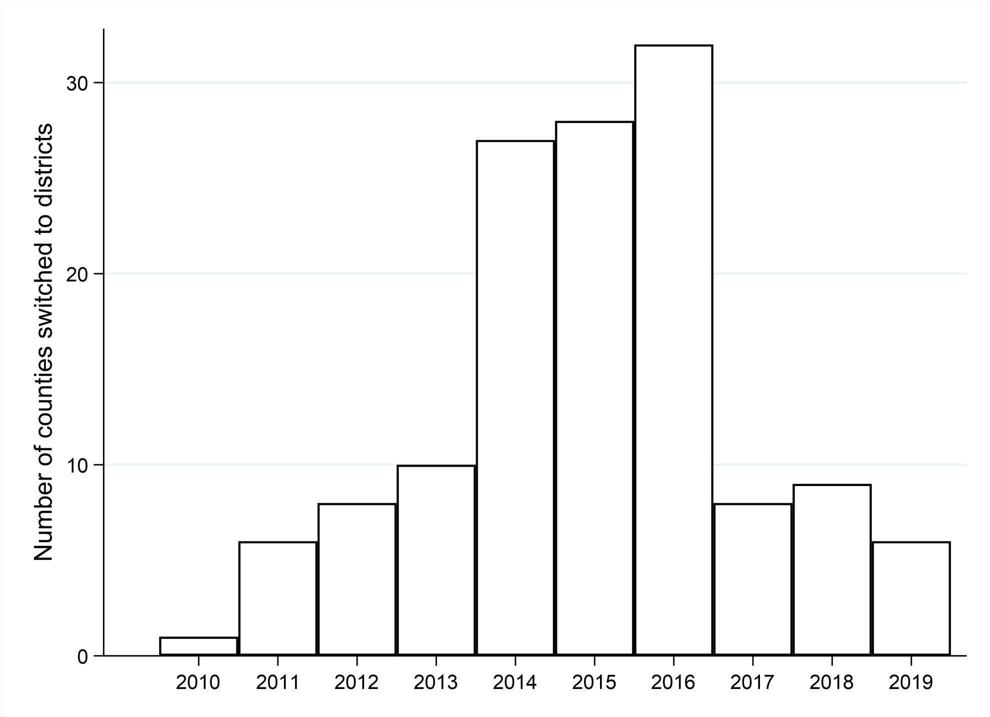
Although counties and municipal districts are both classified as county-level administrative units, they differ significantly in their roles and relationships with higher-level governments. Municipal districts are directly governed by the prefectural government and function largely as its administrative branches. Responsibilities such as urban planning, infrastructure development, and land management in districts are typically carried out by the prefectural government. In contrast, county governments enjoy greater autonomy and are independently responsible for these functions, albeit under general prefectural oversight. This institutional difference is also reflected in fiscal arrangements: districts contribute a larger share of revenue to, and receive more public investment from, the prefectural government than counties do.

The central government assigns distinct economic development roles to municipal districts and counties. As the political and economic centers of prefectures, districts focus on developing secondary and tertiary industries. Peripheral counties, by contrast, retain a stronger emphasis on the primary sector—agriculture, forestry, and fishing—which remains a key priority of county governments. These functional distinctions are mirrored in land use policy. To protect farmland, the central government imposes quotas on land that can be converted to non-agricultural use, typically allocating larger quotas to districts to support their development targets. When a county is annexed into a central city, the newly formed district often gains access to higher land quotas, enabling an expansion in the supply of urban land.

B. Cases of annexation

Figure A.1 illustrates the yearly number of counties in our sample that were converted into municipal districts and incorporated into central cities between 2010 and 2019. The full sample includes 135 counties that underwent such conversion during this period. To ensure comparability across provinces, we exclude counties from the four province-level municipalities under direct central government control, including Beijing, Chongqing, Shanghai, and Tianjin. We also exclude counties from Xinjiang and Tibet, which differ significantly from other provinces in terms of geography, administrative systems, culture, and economic policies. After these exclusions, our analysis sample consists of 97 treated counties. The control group includes 155 counties that are adjacent to central cities but were not annexed during the sample period. Across these treated and control counties, we observe over 56,000 industrial land transactions during the study period.

Figure A.1: Annual number of counties annexed into central cities



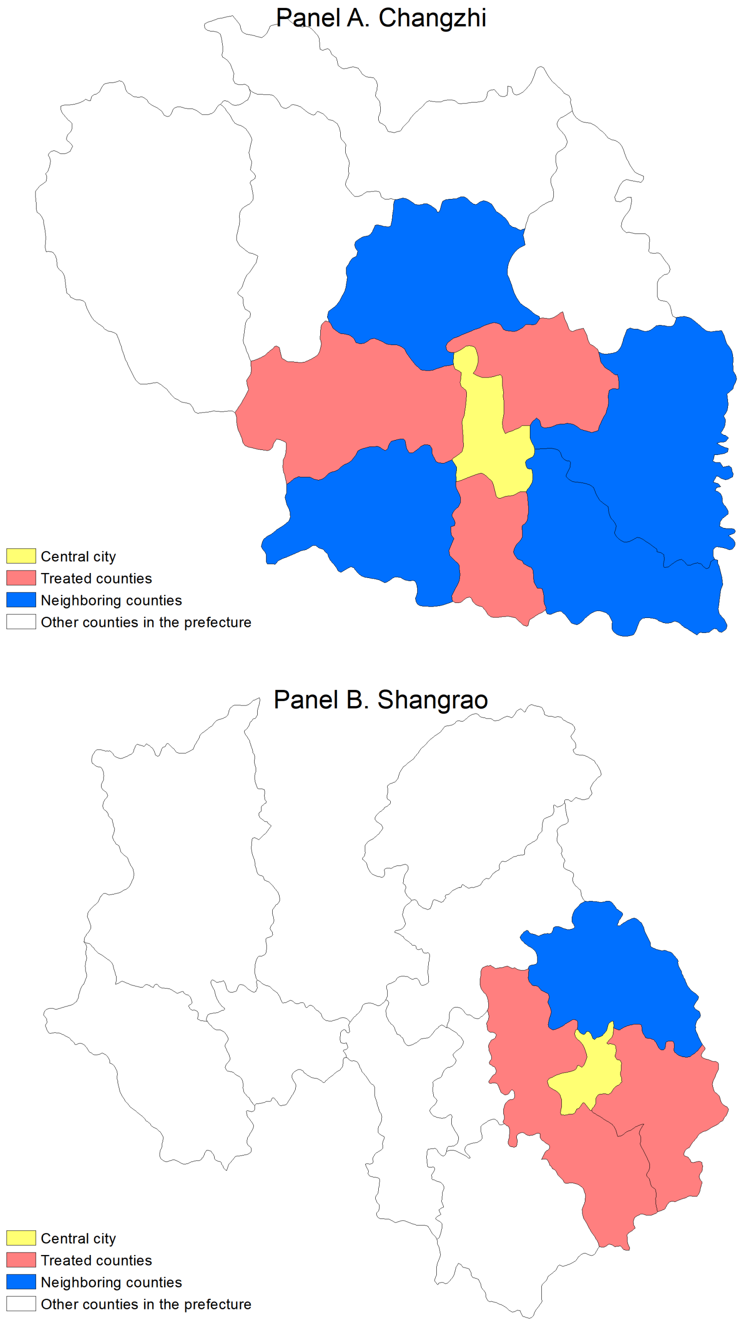
Notes: These numbers are calculated using data from the Ministry of Civil Affairs.

Figure A.2 illustrates two representative annexation cases under the DUG policy: the prefecture-level cities of *Changzhi* in Shanxi Province and *Shangrao* in Jiangxi Province. In each map, the yellow area denotes the central city as of 2010, the start of our sample period. Red areas indicate counties that were reclassified as municipal districts between 2010 and 2019. Blue areas are counties adjacent to the central city that remained unannexed through 2019, while white areas represent other peripheral counties within the prefecture.

In 2019, *Shangrao* consisted of 12 county-level units: three municipal districts comprising the central city and nine peripheral counties. *Changzhi* included four districts and eight counties. As shown in Figure A.2, the newly annexed districts—*Shangdang*, *Tunliu*, and *Lucheng*) in *Changzhi*, and *Guangfeng* and *Guangxin*) in *Shangrao*—are all adjacent to the original central city.

For example, prior to 2015, the central city of *Shangrao* consisted of a single municipal district, *Xinzhou*. To accommodate rapid urbanization and industrial growth, *Guangfeng* county and the *Shangrao* county were reclassified as *Guangfeng* district in 2015 and *Guangxin* district in 2019, respectively.

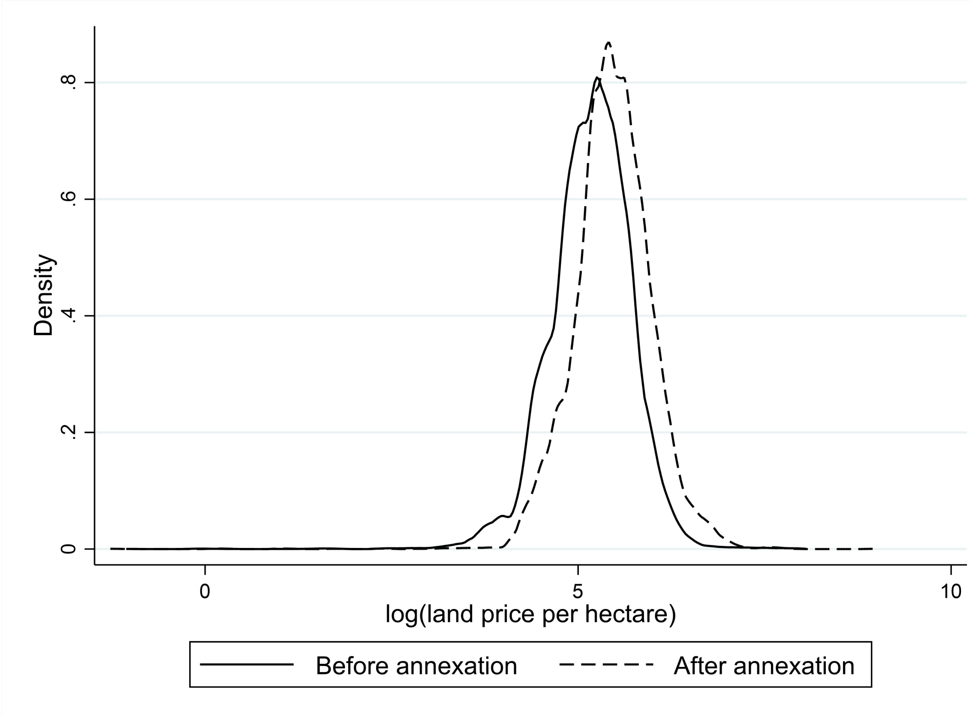
Figure A.2: Examples of the annexation: Changzhi and Shangrao



Notes: Panel A is the map of Changzhi in Shanxi Province and Panel B is the map of Shangrao in Jiangxi Province. The yellow areas represent the central city in 2010, the red areas represent the annexed counties during the sample period (2010–2019), the blue areas represent the counties that are adjacent to the central city but have not been annexed into the central city, and the white areas represent other counties in the prefecture.

C. Results of the event study using no control group

Figure A.3: Industrial land prices before and after annexation in annexed counties



Notes: All land prices are adjusted to the 2010 price level using provincial CPIs.

In addition to the baseline DID estimates presented in the main text, we estimated Equations (7) and (8) using data from the annexed counties only, identifying the price effect by comparing industrial land prices before and after annexation. Before conducting econometric analysis, we visualize the patterns of the key outcome variable in Figure A.3. Using data from treated counties, the figure displays the distribution of industrial land prices before and after annexation. The horizontal axis plots the log of industrial land prices, and the vertical axis shows the density. The solid line and the dotted line represent the price density of land transacted before and after annexation, respectively. The rightward shift in the distribution indicates that industrial land prices increase significantly following annexation, under the direction of upper-level governments.

We next present the regression results. Table A.1 reports the estimated coefficients on DUG from Equation (7), using data from annexed counties only and controlling for the same covariates as in Table 3. Figure A.4 plots the coefficients of the year-distance indicators from Equation (8), using the year before annexation as the reference. Both

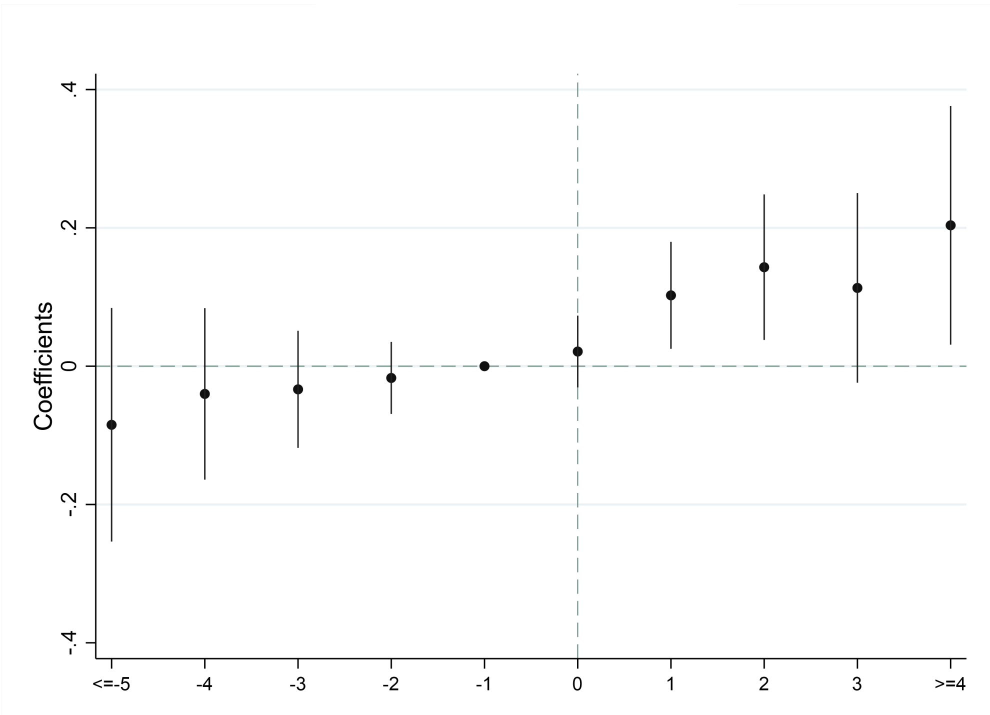
Table A.1 and Figure A.4 show that the event study results (using no controls) closely align with the main DID estimates.

Table A.1: Results from event-study estimation using data from annexed counties only

DV: Log industrial land price	(1)	(2)
DUG	0.0716**	0.0699***
	(0.0311)	(0.0237)
Parcel-level controls	No	Yes
Price_trend	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	23956	23956
Adjusted R^2	0.667	0.711

Notes: This table reports the results of an event-study estimation using data from treated counties only. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Price trend is controlled by the interaction terms between year dummies and the county's median land price in 2010. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.4: Dynamic effects of annexation estimated from the event study



Notes: This figure plots the coefficients of year distance indicators estimated from Equation (8), using data from annexed counties only. Control variables included are the same as those in Table 3 (see notes under the table). The dots represent the values of estimated coefficients, and the vertical lines represent the 95 percent confidence intervals.

D. Robustness checks: initial characteristics of counties

A relevant concern is that unobserved initial county characteristics may affect both the implementation of annexation and industrial land prices, leading to omitted-variable bias. For instance, a county with well-developed manufacturing sector may exhibit higher land prices and be more likely to be annexed. To address this concern, we further include some initial county characteristics in (9), including population, GDP, industrial structure (measured by the share of the secondary sector in GDP), and urbanization rate (measured by the share of the non-agricultural population in total population). To allow these characteristics to have time-varying effects, we interact their 2010 values—the beginning of our sample period—with year fixed effects.

Table A.2 reports the results. Columns (1) and (2) report the coefficients estimated from the event study and the DID method, respectively. The coefficients of interest are similar to those reported in Table 3 in terms of both their magnitudes and significance levels. Therefore, our result that annexation raises industrial land prices is robust to including more county-level controls.

Table A.2: Robustness checks: initial characteristics of counties

DV: Log industrial land price	(1)	(2)
DUG	0.0839***	0.0760***
	(0.0204)	(0.0240)
County characteristics in 2010 × Year dummies	Yes	Yes
Parcel-level controls	Yes	Yes
Price_trend	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	23955	56618
Adjusted R^2	0.715	0.732

Notes: This table reports the results after controlling the county-level characteristics in 2010 times year dummies. Column (1) presents the results of the event study using the sample of treated counties incorporated into central cities. Column (2) reports the result of the DID estimation by defining the control group as treated counties' neighboring counties that are adjacent to the central city. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Price trend is controlled by the interaction terms between year dummies and the county's median land price in 2010. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E. Alternative heterogeneity-robust DID estimators

The treatments in our analysis sample occurred in different years. It is by now well-known that the standard two-way fixed effect estimator as in Equation (7) is a weighted average of all possible two-county-two-period DID estimators in the sample. Surprisingly, an early-treated county may get negative weights if it serves as a "control" for many later-treated counties (Goodman-Bacon 2021). Following the diagnostic approach proposed by de Chaisemartin and D'Haultfœuille (2020), we find little if any negative weights in our baseline estimation, suggesting that the varied timing of treatment is unlikely to have seriously biased our baseline estimates.

Despite the favorable diagnosis, we tried five alternative heterogeneity-robust DID estimators as robustness checks. The primary issue with the baseline two-way fixed-effect approach is the "forbidden comparisons" between units treated later and those already treated. To avoid such comparisons, the alternative estimators employ different strategies. Four of the five alternative estimators pair treated counties in each cohort with a group of "clean" controls and then aggregate cohort-specific DID estimates into overall effects. Specifically, we divide treated counties into different cohorts based on the treatment year, using never-treated adjacent counties as the control group for each cohort. The first method follows the approach used by Cengiz et al. (2019), stacking different cohorts to estimate DID coefficients. Gardner et al. (2024) point out that this approach estimates a weighted average of cohort-specific average treatment effects, with weights determined by relative cohort size and the variance of treatment status within each cohort. The other three approaches—proposed by Sun and Abraham (2021), Callaway and Sant'Anna (2021), and de Chaisemartin and D'Haultfœuille (2024)—aggregate cohort-specific DID estimates using different weighting schemes. We also tried a fifth alternative estimator, using the imputation method by Borusyak et al. (2024). Here we first fit a two-way fixed-effect model of land price as specified in Equation (8) using untreated counties, then use this model to predict the counterfactual land price for treated counties. Subtracting the counterfactual land price from the actual land price of treated counties yields an estimate of the treatment effect. Results from these alternative methods, shown in Figure 3 in the main text, are broadly consistent with the baseline results, indicating parallel pre-trends and a positive treatment effect. Therefore, the effects on industrial land prices are unlikely to be driven by bias from staggered treatment timing.

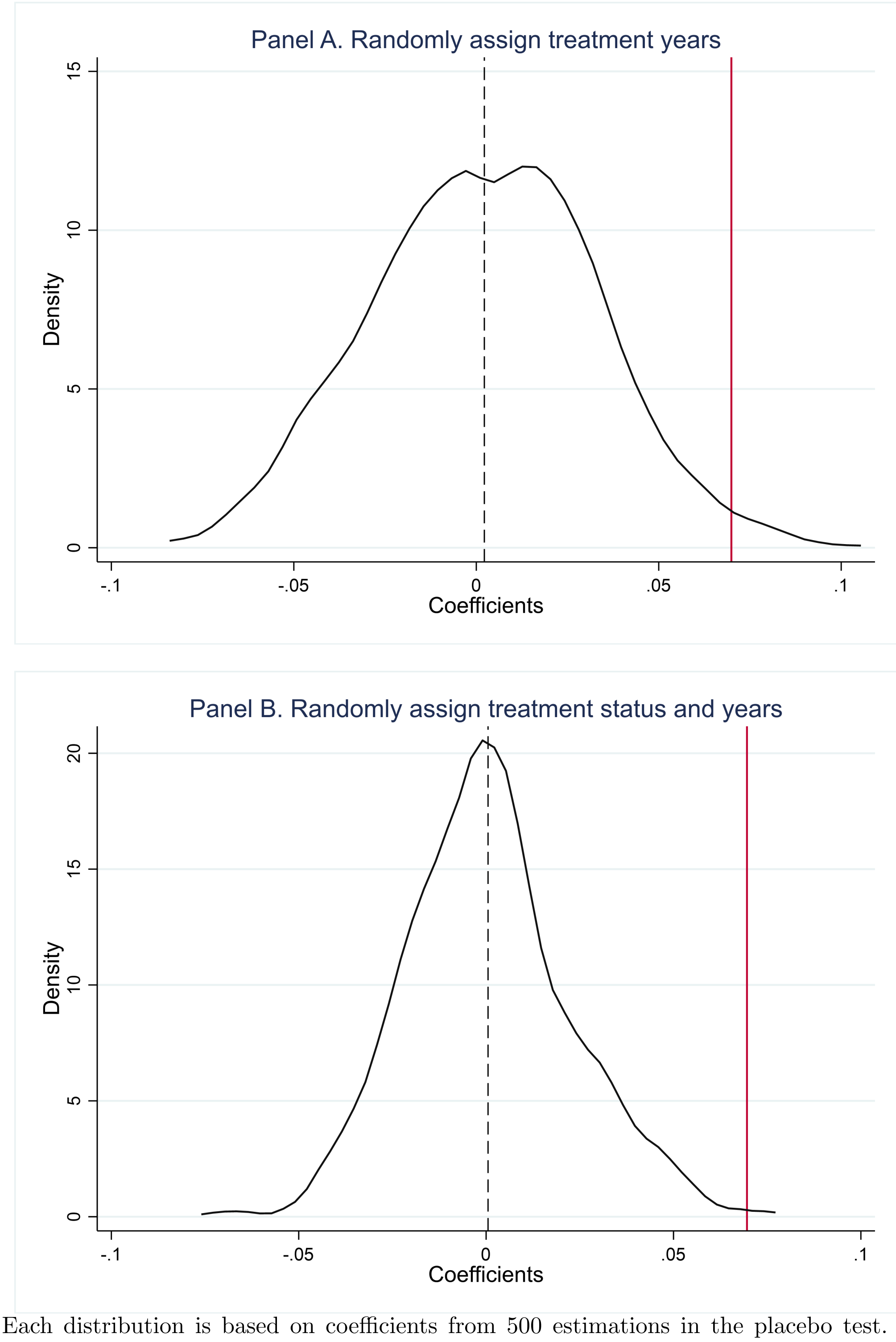
F. Placebo tests

To further address the concern of omitted variable bias, we conducted two placebo tests by randomly assigning annexation timing. First, we randomly assign annexation years to the actual set of treated counties used in Column (2) of Table A.1. Second, using the full sample of 252 counties from Column (2) of Table 3, we randomly assign both the treatment status and treatment year. Specifically, we randomly select 97 counties to form a placebo treatment group and assign each a random treatment year. In both cases, we re-estimate the baseline Equation (7) using these simulated samples..

Figure A.5 summarizes the results based on 500 replications. Panel A shows the distribution of estimated coefficients on the DUG dummy when only the annexation year is randomized among treated counties. The estimates are centered near zero (mean = 0.0022; SD = 0.0304), suggesting no systematic effect. Panel B presents results from the second test, where both treatment assignment and timing are randomized. These estimates also cluster around zero (mean = 0.0005; SD = 0.0217). In both panels, the vertical lines denote the benchmark estimates from the event study (0.0699) and DID estimation (0.0696), which lie at the far right of the distributions and are statistically distinguishable from zero.

Taken together, these placebo tests reinforce that our estimated effects of annexation on land prices are unlikely to be driven by unobserved confounding factors.

Figure A.5: Distribution of estimated coefficients in the placebo tests



Notes: Each distribution is based on coefficients from 500 estimations in the placebo test. Panel A plots the distribution of coefficients when we randomly assign the annexation year for treated counties. Panel B plots the distribution of coefficients when we randomly assign both the treatment status and the treatment year among the sample of both treated and control counties. The red vertical lines represent the benchmark estimates reported in Column (2) of Table A.1 and Column (2) of Table 3.

G. Alternative identification strategies

(i) Using unapproved annexation applicants as control group

Instead of using all other adjacent counties as the control group (as in the main text), we use counties within our sample of prefectures that applied for annexation but were not approved (either rejected or still pending). We identify 37 such counties. The results, presented in Table A.3, show that the key coefficients are only slightly smaller than our baseline estimates.

Table A.3: DID estimation using applied-but-failed counties as control group

	(1) DV: Log land price	(2) DV: Log land price
DUG	0.0685**	0.0470*
	(0.0310)	(0.0277)
Controls		Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	34950	34950
Adjusted R^2	0.688	0.723

Notes: This table reports the effects of annexation on industrial land price with the control group including counties that applied for annexation but were not approved. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We conducted the same balance test as in Table 2 of the main text, comparing treated and control counties along several dimensions. We find that the applied-but-unapproved counties have a significantly lower county-to-city revenue ratio than the treated counties. This supports our suspicion that some adjacent counties that did not apply for annexation may have stronger economies than those that did apply, which explains why the full set of adjacent counties passed the balance test in Table 2. We therefore believe that using all non-treated adjacent counties as the control group is more appropriate.

(ii) Using matched counties as control group

We also constructed a control group using propensity score matching (PSM). From the sample of all counties in China, we identified the closest match for each treated county based on the following four characteristics in 2010: population, GDP, urbanization rate, and the share of GDP from the secondary sector. In total, we obtained 92 matched counties, which we then combined with the treated counties to run DID estimations parallel to our baseline. The results are reported in Table A.4. The coefficient on the DUG dummy is very similar to the baseline estimates, suggesting that the control group used in our baseline is, on average, not very different from this matched group.

Table A.4: PSM-DID estimation using matched counties as control group

	(1) DV: Log land price	(2) DV: Log land price
DUG	0.0652**	0.0704***
	(0.0261)	(0.0243)
Controls		Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	30837	30837
Adjusted R^2	0.659	0.697

Notes: This table reports the effects of annexation on industrial land price with the control group including counties that are matched with treated counties based on four characteristics: 2010 population, GDP, urbanization rate, and the share of second-sector GDP in the total. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(iii) Using synthetic controls

We also implement the Synthetic Difference-in-Differences (Synthetic DID or SDID) approach (Arkhangelsky et al. 2021, Clarke et al. 2023), which combines the strengths of the traditional DID and Synthetic Control methods to improve causal inference in comparative case studies. Specifically, this procedure constructs a synthetic control as a weighted combination of control counties that closely match the treated county's pre-treatment outcomes, and then applies the DID framework to adjust for time-varying confounders. Since the method can only be applied at the county level, we first compute yearly average industrial land prices, using both unadjusted (simple average) and adjusted (based on parcel characteristics) measures. We then estimate the effect of annexation using the SDID method. The results, reported in Table A.4, are consistent with our baseline estimates.

Table A.5: Synthetic DID results

	(1) DV: Log land price (simple average)	(2) DV: Log land price (adjusted for parcel characteristics)
DUG	0.0847**	0.0701**
	(0.0337)	(0.0321)
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	1971	1971

Notes: This table reports the effects of annexation on industrial land price at the county level using the synthetic DID method. In column (2), yearly county level average is calculated controlling for parcel characteristics including transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Bootstrapped (500 times) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(iv) Exploring an instrumental variables (IV) approach

We first use a LASSO procedure to identify strong predictors of annexation. Among 15 different county/city characteristics, we find that log county-city distance is the strongest predictor of annexation status—this makes intuitive sense, as it is easier to convert a geographically closer county into an urban district.

Table A.6: IV estimation 2010-2019

	(1) OLS DV: land price growth	(2) First stage	(3) 2SLS DV: land price growth
DUG	0.0905***		0.3870*
	(0.0330)		(0.2068)
Log county-city distance		-0.2273***	
		(0.0785)	
Controls	Yes	Yes	Yes
Province_FE	Yes	Yes	Yes
Cragg-Donald F statistic			10.11
Observations	238	238	239

Notes: This table reports the effects of annexation on industrial land price estimated at the county level, using log county-city distance as the IV. County-level controls include average elevation, average slope, population, GDP, share of second-sector GDP, and urbanization rate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We then experiment with using county-city distance as an instrument for annexation. Since this distance is time-invariant, we cannot use panel estimation; instead, we regress land price growth on annexation status in a cross-sectional setting. For each county, we calculate the growth in industrial land price as follows:

$$growth_i = \ln(LandPrice_{i,pre}) - \ln(LandPrice_{i,post}),$$

where $LandPrice_{i,pre}$ and $LandPrice_{i,post}$ are the average land prices before and after annexation, respectively, after controlling for land parcel characteristics, county fixed effects, and province-year fixed effects. We then regress this price growth on annexation status using 2SLS, assuming that log county-city distance affects land price growth only through its effect on annexation (see Table A.6).

While the IV estimate is positive, it is about four times larger than the OLS estimate. One could interpret this as evidence that the OLS estimate is biased downward; however, we believe it is more likely that the distance variable violates the exclusion restriction.

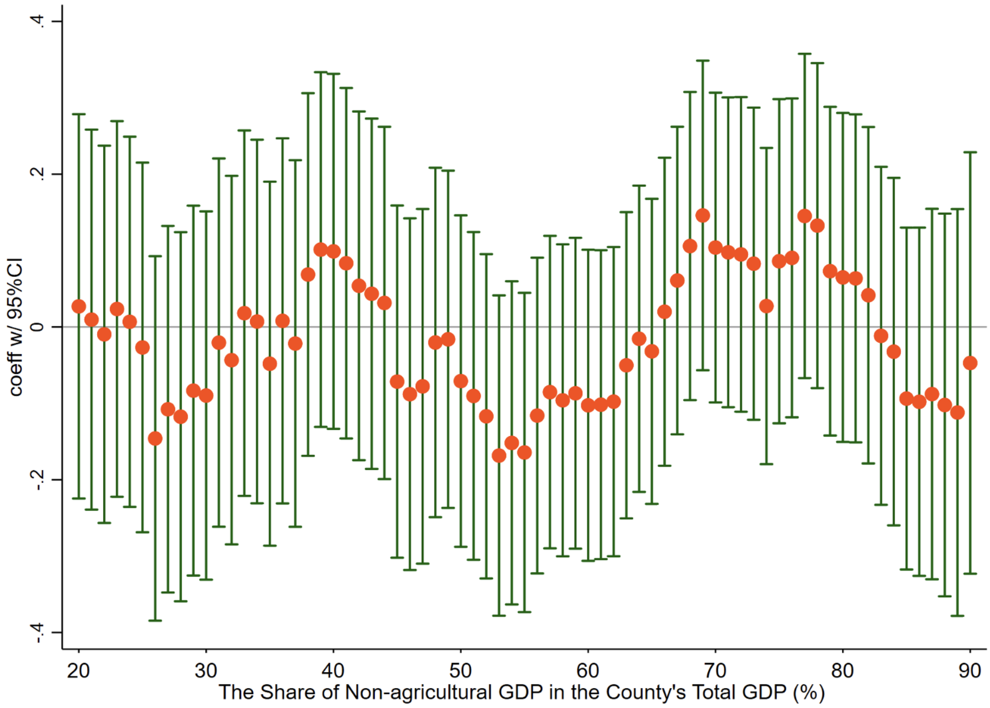
(v) Detecting potential policy cutoffs

Following a referee's suggestion, we explore whether a regression discontinuity (RD) design is feasible. For example, if the decision to annex was based on a cutoff criterion, an RD approach may allow us to identify the causal effect of annexation. For each treated or control county, let x represent a county characteristic in the year before annexation that may have influenced annexation decisions—for example, the share of non-agricultural GDP in total GDP (%). Let x^* be a potential policy cutoff and define $1_{\{.\}}$ as an indicator variable. We estimate the following county-level regression:

$$1_{\{\text{county} c \text{ is annexed}\}} = \alpha + \beta \cdot x_c + \gamma \cdot 1_{\{x_c > x^*\}} + \varepsilon_c.$$

Because more industrialized counties are more likely to be annexed, we expect $\hat{\beta}$ to be statistically significant. If a consistent policy cutoff x^* was applied, then $\hat{\gamma}$, should also be statistically significant. To systematically test for a cutoff, we loop through different values of x^* (e.g., from 20% to 90% in 1% increments, for a total of 71 regressions). We then identify the x^* that yields the highest R^2 and check whether the corresponding $\hat{\gamma}$ is statistically significant. Figure A.6 plots $\hat{\gamma}$ against each assumed cutoff for the non-agricultural GDP share. None of them is statistically significant.

Figure A.6: Estimated coefficients of indicator of assumed policy cutoffs



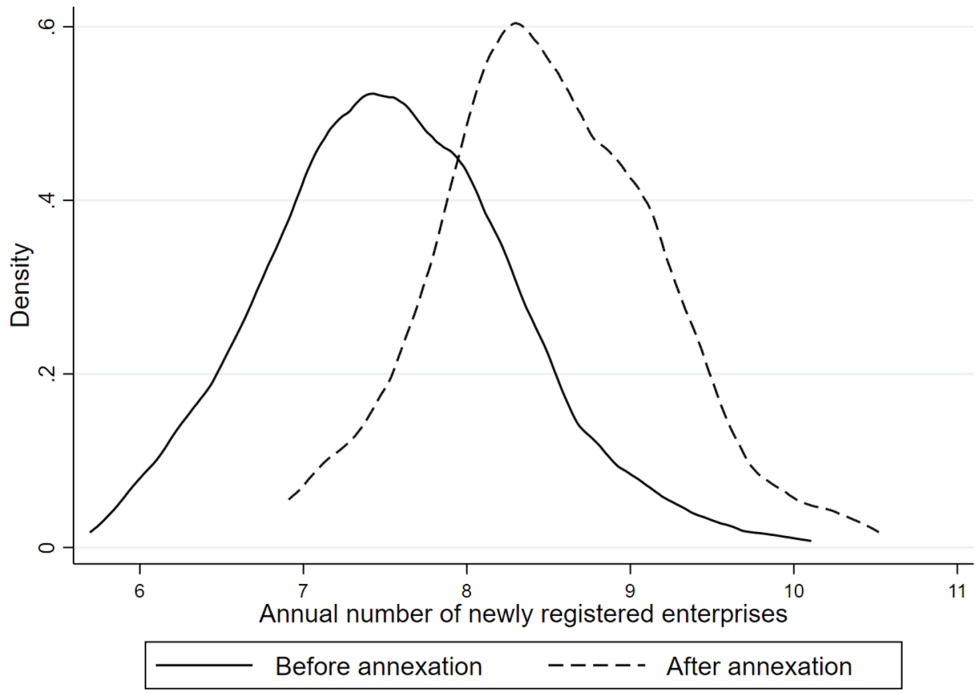
Notes: This figure shows the estimated coefficient on a dummy variable indicating whether a county's non-agricultural GDP share exceeds a given cutoff. The values on the horizontal axis represent the assumed policy cutoffs.

We also repeated the analysis using the county-to-city revenue ratio and county-to-city GDP ratio, both of which appear to affect annexation status. However, neither variable revealed a clear cutoff. We therefore conclude that the annexation decision was unlikely to have followed a clear rule that would allow for an RD design.

H. Newly registered enterprises before and after annexation

As a complement to the regression analysis of firm entry in Section 7 of the main text, we present descriptive evidence here. Figure A.7 shows the distribution of the annual number of newly registered industrial and commercial enterprises in treated counties. The solid and dotted lines represent the distributions before and after annexation, respectively. The post-annexation distribution clearly shifts to the right, suggesting that annexation is associated with an increase in firm entry.

Figure A.7: Distribution of newly registered enterprises before and after annexation



Notes: This figure plots the distribution of the annual number of newly registered enterprises before and after annexation. The annual number is calculated using the SAMR data that spans the period 2010-2019.

I. Government practices in land markets

A potential alternative explanation for rising land prices is the relaxation of government intervention following annexation. In China, upper-level governments evaluate local officials based on economic performance, creating strong incentives for local leaders to attract investment. County leaders, who enjoy greater administrative autonomy than district officials, often resort to non-market land transfers—such as administratively allocating industrial land at below-market prices—as part of this strategy. This is a key reason why we control for land transaction modes in our baseline land price regressions.

To explore whether annexation shifted land transactions toward more market-oriented mechanisms, we examine whether the use of auctions—the primary competitive allocation method—increased following annexation. If so, greater reliance on auctions could contribute to higher post-annexation land prices.

Table A.7 reports regression results using two dependent variables: the share of transaction events using auctions as well as the share of land area transacted through auctions. Columns (1)-(2) present DID estimates based on the full sample, including both treated and control counties. The coefficients on the DUG indicator are small in magnitude (about 2 %) and either marginally significant or statistically insignificant. Thus, the increase in land prices in annexed relative to control counties cannot be attributed to reduced administrative interference through increased auction use.[1]

Table A.7: Effects annexation on land transaction modes

	(1)	(2)
Dependent variable:	Share of transactions through auctions	Share of transaction area through auctions
DUG	0.0215*	0.0173
	(0.0121)	(0.0120)
Controls	Yes	Yes
County_FE	Yes	Yes
Province_Year_FE	Yes	Yes
Observations	2365	2365
Adjusted R^2	0.221	0.194

Notes: This table reports the effects of annexation on land transaction modes. Columns (1) and (2) present the result of the DID estimation by defining the control group as treated counties' neighboring counties that are adjacent to the central city. The dependent variable in Column (1) is the share of transactions using auctions in the count of total transactions. Column (2) is the share of transaction area using auctions in total area. Standard errors are clustered at the county level. Controls include the following 2010 county/district characteristics: log population, log GDP, share of second-sector GDP in total GDP, and urbanization rate. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

J. Effects of annexation on residential and commercial land prices

We conduct a parallel analysis to assess the effects of annexation on residential and commercial land prices. Results are reported in Table A.8. Following the baseline specification, we control for parcel-level characteristics, including transaction mode dummies, land grade, parcel size, leasehold length, approval authority, and distance to the county center. To account for price trends, we include interactions between year dummies and the county's median land price in 2010.

[1] One might also suspect that increases in industrial land prices result from a decreased land supply following the annexation. To test this, we examine whether the total volume of industrial land transactions or the industrial share of total transacted land declined after annexation. For both the event study and the DID specifications, the coefficients of the DUG dummy are never statistically significant and are positive in three out of four regressions, suggesting that decreased land supply is unlikely an explanation for increases in industrial land prices. Results are available upon request.

Column (1) of Table A.8 shows that annexation leads to a significant increase in residential land prices. In contrast, Columns (2) and (3) indicate that annexation has no significant effect on commercial land prices or on the combined category of residential and commercial land.

Table A.8: Effects on residential and commercial land prices

	(1)	(2)	(3)
D.V.: ln(land price)	Residential land	Commercial land	Residential +commercial land
DUG	0.1289*	-0.0536	0.0845
	(0.0774)	(0.0522)	(0.0612)
Parcel-level controls	Y	Y	Y
Price_trend	Y	Y	Y
County_FE	Y	Y	Y
Province_Year_FE	Y	Y	Y
Observations	65,218	23,743	88,964
Adjusted R^2	0.688	0.499	0.634

Notes: These analyses parallel those reported in Table 3 in the main text. Columns (1), (2), and (3) report the results of the DID estimation by defining the control group as treated counties' neighboring counties that are adjacent to the central city. Parcel-level controls include transaction mode dummies, land grade, land area, leasehold length, level of the government that approved the land transaction, and distance to the county center. Price trend is controlled by the interaction terms between year dummies and the county's median land price in 2010. Standard errors are clustered at the county level. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.