Price and Volume Divergence in China's Real Estate Markets: The Role of Local Governments*

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Abstract

During the Covid-19 pandemic (2020-2022), Chinese cities witnessed a paradox: residential land and property prices surged even as transaction volumes plummeted. This divergence wasn't due to supply shortages. Instead, we attribute it to active management of land and housing prices by local governments. Cities that had been more reliant on land sales and land-collateralized debt to fund their budgets before the pandemic experienced greater increases in land prices. Moreover, Local Government Financing Vehicles (LGFVs) procured more land at higher prices compared to other buyers. These findings underscore the significant roles local governments play in shaping real estate markets in China.

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The real estate sector is crucial for economic health, particularly because real estate properties serve as primary collateral for financing firm investments. This role has been emphasized by Chaney, Sraer, and Thesmar (2012), and Liu, Wang, and Zha (2013). In China, the impact of this sector is even more significant. According to Rogoff and Yang (2021), real estate investment in China contributes approximately 10% to its GDP and supports over 15% of urban employment.

However, the onset of the Covid-19 pandemic marked a turning point for China's real estate market, leading to an unprecedented downturn, as reflected by a series of debt defaults by major Chinese real estate developers such as Evergrande, Country Garden, and Sino-Ocean. This financial distress has been compounded by issues like a surplus of vacant housing units in various cities (e.g., Glaeser, Huang, Ma, and Shleifer (2017) and Liu and Xiong (2020)) and overbuilding, especially in third-tier cities, as noted by Rogoff and Yang (2022). These challenges have raised significant concerns about a potential real estate crisis with ensuing implications for the financial and economic stability of the world's second-largest economy.

This real estate downturn in China stands in stark contrast to the usual pattern observed in downturns, where both prices and transaction volumes typically fall. Instead, in this unique cycle, residential land and property prices have risen significantly, even as transaction volumes have sharply decreased. This unusual divergence is captured in Figure 1, which summarizes data from 173 Chinese cities—four first-tier cities, 45 second-tier cities (including provincial capitals and major cities), and 124 smaller cities—spanning from 2017 to 2022. Panel A of the figure showcases the trends in land prices alongside the annual growth rates in the transaction volume for residential land designated for housing developments. The aftermath of the Covid-19 outbreak saw these cities facing notable declines in the volume of residential land transactions, with annual transaction areas falling by approximately 10% and 23% in 2021 and 2022, respectively. In contrast, during these years, land prices in the cities surged, marking a clear deviation from the declining transaction volumes.[1] Panel B illustrates a similar divergence in the market for new

[1] We calculate annual land prices by dividing the total transaction volume, expressed in Renminbi, by the total transacted area in these cities. We refrain from directly charting the total transaction volumes due to incomplete data for certain cities in some years. To further substantiate the divergence between prices and transaction volumes, we will provide more detailed regression studies, taking into account diverse characteristics of cities and transactions.

housing units, where prices escalate despite a decline in the volume of transactions.

The divergence between price and volume during this downturn in China's real estate market is indeed puzzling, especially when analyzed through the lens of conventional demand and supply dynamics. Typically, demand-side factors are expected to influence both price and volume concurrently, leading to parallel movements in these variables. However, what we observe in this cycle is a significant increase in prices alongside a substantial decrease in transaction volumes. Crucially, this pattern does not appear to be the result of a supply shortage. As we will show, there is a notable rise in failed residential land auctions in 2021 and 2022 across Chinese cities. This finding indicates that there is no acute scarcity of land supply that could justify such a price increase, thus ruling out the usual supply constraint as a primary driver of the increasing prices.

The downturn in China’s real estate sector thus presents a compelling case for exploring the economic mechanisms influencing its market dynamics. A critical aspect of our analysis involves understanding the significant role of local governments, who are key players in the sector due to their constitutional control over land. This control becomes even more crucial in the context of urban development in China, where local governments are constrained from leveraging property taxes to finance their extensive infrastructure initiatives. Instead, they depend heavily on revenue from land sales, which contributed to 38% of local government budgets in 2019.

Moreover, land serves a dual role in the financial strategies of local governments. It is not only a source of revenue but also a critical asset used as collateral for debt acquisition through Local Government Financing Vehicles (LGFVs). LGFVs are instrumental in funding various local infrastructure and development projects, further linking the health of the real estate sector to the financial capacity of local governments. Additionally, real estate properties play a central role as collateral for corporate debt financing. Therefore, real estate prices also affect the overall stability of the local economy, which also falls under the responsibility of local governments.

Given these dynamics, we hypothesize that local governments, grappling with the economic repercussions of the Covid-19 pandemic and the necessity to manage their debt obligations, might have strategically managed land prices. This strategy would be especially pertinent for cities that, prior to the pandemic, were more dependent on revenues from land sales and the use of land as collateral for debt to finance their fiscal budgets.

To test this hypothesis, we adopt a dynamic difference-in-differences approach by comparing land price changes between cities with varied fiscal dependencies on land sales and different debt burdens. A city's fiscal reliance on land sales is measured by the proportion of land sales revenue to its total fiscal income in 2019, right before the onset of Covid-19. Using data from 104,070 residential land transactions across 173 cities between 2017 and 2022, we executed a transaction-level regression of the transaction price against the city's fiscal dependence, year dummies for 2017, 2018, 2020, 2021, and 2022, and especially, the interaction of fiscal dependence with these year dummies, alongside controlling for a host of city and land characteristics. Remarkably, our analysis revealed that cities with greater fiscal dependence on land sales witnessed notably higher prices in 2021 and 2022, compared to 2019.

Furthermore, by measuring each city's debt burden as the cumulative debt of all LGFVs in a city against the city's total fiscal revenue in 2019, we also find that those cities with significant debt burdens experienced higher land prices in 2021 and 2022 compared to 2019. Collectively, these nuanced findings from the difference-in-differences analysis substantiate the hypothesis that local governments' fiscal conditions play a crucial role in driving local land prices.

Local governments potentially moderate land prices by adjusting land supply, yet our study unveils another mechanism via LGFVs' land acquisitions. Pre-pandemic, LGFVs maintained a stable acquisition share, but during the pandemic, their share in residential land acquisitions significantly escalated, rising from 14.2% of all residential land transactions in 2019 to 32.2% in 2022. Intriguingly, prior to the pandemic, LGFVs acquired land at prices 8.1% lower than other buyers in 2019; however, post-pandemic, especially in 2022, they paid 14.9% higher prices. This blend of countercyclical acquisitions and elevated bidding by LGFVs highlight their crucial role in bolstering land prices during the pandemic. Further, we corroborated that LGFVs' leverage notably augmented in the pandemic years, mirroring their aggressive land acquisitions.

Local governments have also actively managed prices of new housing units during this period.

Our analysis shows that in 2022, there was a marked reduction in the issuance of permits for selling new housing units across Chinese cities, a move that directly constrained housing supply. Moreover, a number of cities, primarily those classified as third-tier cities that experienced significantly diminished housing demand, introduced administrative restrictions in 2021-2022, which prohibit developers from pricing new housing units below designated benchmarks.

Taken together, our study not only identifies the price-volume divergence as a novel characteristic of China's real estate downturn but also highlights the proactive and strategic role of local governments in shaping these market dynamics. This insight is pivotal for understanding the economic mechanisms driving China's real estate sector and for evaluating its future development.

Commentators have drawn parallels between China's seemingly overheated real estate sector and the U.S. experience during the mid-2000s. However, these two cases are fundamentally different. The U.S. housing bubble was largely driven by a credit expansion, fueled by the securitization of mortgages, particularly targeting subprime households (Mian and Sufi, 2009). In contrast, as discussed by Xiong (2023), the real estate boom in China over the past three decades, can be attributed to a distinctive hybrid real estate model. This model is marked by the practice of local governments utilizing revenue from land sales, along with debt secured by land, to fund local infrastructure projects. The investment in infrastructure, in turn, stimulates urban development and propels the real estate market forward, creating a symbiotic relationship between land management, infrastructure growth, and real estate expansion.

Our study contributes to this discussion by providing systematic empirical evidence of the active interventions of local governments in managing land and housing prices during the pandemic. By supporting real estate prices, local governments can sustain their own debt financing and that of local firms, which also heavily rely on real estate assets as collateral. Nonetheless, these interventions, while aimed at market stabilization, could inadvertently distort market prices. This, in turn, might suppress consumer demand for housing and hinder real estate developers' capacity to sell newly constructed units, thereby affecting their ability to service their debts.

Our findings offer several insights about China's real estate sector. Firstly, the availability of residential land and the ensuing development of residential properties in Chinese cities are not solely governed by geographical and zoning constraints, a concept highlighted by studies focusing on real estate supply in Western cities, such as Saiz (2010) and Glaeser and Gyourko (2018). Instead, the supply is profoundly influenced by the strategic maneuvers of a monopolistic land seller, whose decisions are shaped by its policy objectives and financial conditions.

Secondly, our study unveils a novel mechanism by which local governments in China strategically influence the behavior of real estate prices during economic downturns. The standard real estate market frictions, such as sellers' disposition effect (Genesove and Mayer, 2001), buyers' downpayment effect (Stein, 1995), search frictions (Wheaton, 1990; Guren, 2018), buyers' extrapolative behaviors (Glaeser and Nathanson, 2017), and land hoarding and investment home purchases by speculators (Nathanson and Zwick, 2018; Gao, Sockin, and Xiong, 2020; DeFusco, Nathanson and Zwick, 2022) do not adequately explain the price-volume divergence observed in China's recent real estate downturn, especially in the primary land market. In this centralized market, the sellers, typically local governments that own the land by constitution, are not subject to these frictions. Our study proposes an alternative explanation: in Chinese cities, local governments have a strong incentive to maintain or even increase real estate prices to support their own land-based debt financing and that of firms. This mechanism may also help explain the misallocation of finance in the Chinese economy, as highlighted by Whited and Zhao (2021).

Finally, our analysis also sheds light on the issues related to high debt levels in China. The recent high-profile debt defaults by entities like Evergrande, Country Garden, and Sino-Ocean have directed attention to the financial distress of real estate developers. However, our study highlights a potentially deeper debt problem related to local governments. This problem has significantly affected transaction price and volume of residential land and properties, exacerbating the financial distress of real estate developers.

This insight aligns with a key theme highlighted by Song and Xiong (2023), emphasizing that the career incentives fostered by economic tournaments within China's state system can cultivate a penchant for short-termism amongst local government officials, propelling local governments towards overinvestment and excessive leverage. It's also important to differentiate our emphasis on structural challenges faced by local governments from the studies of rampant corruptions in China's land market, such as Cai, Henderson, and Zhang (2013), Chen and Kung (2019), and Fang, Gu, and Zhou (2019).

I. Institutional Background

In this section, we provide an overview of China's land market and elucidate the significance of land sales and land-based debt financing to the fiscal budget of local governments.

A. China's Land Market

In China, land is not privately owned. According to the constitution, all land is owned by the state. For several decades after the founding of the People's Republic of China in 1949, land transactions were prohibited. However, a pivotal constitutional amendment in 1988 allowed transactions of "land usage right" for a stipulated duration, which are usually called land transactions in China, paving the way for housing privatization.

China implements stringent zoning regulations to designate specific land parcels for particular purposes: industrial land is earmarked for industrial and manufacturing projects, residential land for housing, and commercial land for business establishments. As per the prevailing land laws, industrial land can be leased for up to 30 years, commercial land for 40 years, and residential land for 70 years.[2] Through its Ministry of Land and Resources, the central government enforces a strict annual cap on the aggregate area of land that can be appropriated for commercial and residential purposes. This quota is then distributed among various regions. Regional governments are tasked with selling land within this allocation.

In an effort to foster transparency and fairness in the land market, all transactions involving

[2] Local governments in China frequently employ a dual strategy in land sales: they tend to offer industrial land at discounted prices as an incentive to entice companies, particularly prominent ones, to establish operations within their jurisdictions. Conversely, residential and commercial land is often sold at considerably higher prices as a means to finance local development projects and initiatives. He et al. (2022) delve into the strategic motivations and implications behind such practices by local governments.

commercial and residential land must be conducted using market mechanisms.[3] These include invitations to tender (招标);[4] auctions (拍卖);[5] and listings (挂牌).[6] Since the volume of secondary land transactions is minimal relative to the primary market, municipal governments are the predominant land providers. These governments have the power to influence land prices by modulating the supply. The relatively low barriers to entry in the primary land market have enticed numerous enterprises to venture into real estate, instigating competition among buyers. The highest bidder is granted the land use rights. Extensive analyses of China's land market can be found in works by Chen and Kung (2019), Fang, Gu, and Zhou (2019), and Gyourko et al. (2022).

B. Land-Based Finance for Local Governments

Over the past four decades, China has undergone a significant urbanization wave, with hundreds of millions migrating from rural to urban areas. Throughout this process of urban development, Chinese cities have faced the challenge of providing necessary infrastructure and housing without the ability to fund these projects through property taxes, a common method in many Western cities. This limitation stems from the fact that, at the onset of urbanization, all real estate properties were state-owned. In response, Chinese cities adopted a distinctive approach to finance public infrastructure: leveraging land sales and land-based financing. This model has played a crucial role in supporting the rapid urban development observed across the country, as discussed by Liu and Xiong (2020).

Local governments repossess land from farmers and urban residents, subsequently selling it to developers and businesses (Zhang and Barnett, 2014; Ambrose et al., 2015; Fang et al., 2016). By 2019, revenue from these land sales had morphed into a critical fiscal pillar, making up over 50% of the total fiscal revenue in some regions, as extensively discussed by Gyourko et al. (2022).[7]

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[3] China's Ministry of Land and Resources document No. 71 in 2004.

[4] Invitation to tender involves local government inviting individuals or institutions to bid on a given piece of land. The land use right is granted according to the outcome of the bidding.

[5] Auction allows bidders to participate at a designated time and place. Bidders quote their bidding prices publicly and the user of the land is determined according to their bidding prices.

[6] Listing is a process in which the local government places an announcement in a designated land exchange. The grantor must disclose the terms and conditions for granting the land use right. Once quotations from bidders are accepted, updates will be made in the listing announcement accordingly. The land use right is granted based on the quotation made at the end of the notice period, which must be at least 10 working days.

[7] Li et al. (2023) use the US-China trade war as an external shock to China's real estate market, allowing them to estimate the effect of this market disruption on China's land-based public finance.

Even though budget laws restrict how much local governments can accrue deficits and acquire loans from banks or financial markets, they may also borrow indirectly through Local Government Financing Vehicles (LGFVs). LGFVs are essentially state-owned enterprises controlled by corresponding municipal governments. Initially, LGFVs were confined to limited financing activities. However, the global financial crisis in 2008 and the ensuing fiscal stimulus plan (2008-2010) relaxed these constraints, allowing local governments to sidestep budget laws through LGFVs and to undertake substantial bank loans and bond issuances, as extensively discussed by Bai et al. (2016) and Chen et al. (2020). Even though local governments are not legally obligated to assume LGFV debts, LGFV borrowing is commonly viewed as off-balance-sheet debt of local governments.

China's distinctive political-economic structure (Li and Zhou, 2005; Xu, 2011; Song and Xiong, 2023) motivates local government officials to prioritize economic development. Investing in Local GDP growth is deemed the most effective method to achieve this. The green-lighting of LGFVs for financing has led local governments to be deeply involved in the real estate industry, with a significant slice of their revenue derived from land sales, either by selling land to property developers or using it as collateral. This practice has persisted and intensified even post-stimulus plan, demonstrating the integral role of LGFVs in the economic strategies of local governments.

The outbreak of the Covid-19 pandemic in February 2020 deeply impacted the Chinese economy, as well as the fiscal conditions of its local governments. China implemented strict zero-Covid measures, mandating regular testing for residents and imposing mobility and operational restrictions in areas with detected infections. Until these measures were finally removed in December 2022, local governments bore the financial burden associated with implementing the zero-Covid policy. The combined effects of decreased tax revenue from 2020 to 2022 due to the economic slowdown and the significant expenses of enforcing these stringent health protocols resulted in a strained economy and pronounced budget deficits for many local governments. This fiscal environment set the stage for our analysis of local governments' engagements in the real estate sector, a pivotal alternative for generating fiscal revenue.

As an illustration, in Appendix Table B, we present the fiscal budget, land sales revenue, and total debt of Local Government Financing Vehicles (LGFVs) for four cities in 2022. This includes two large cities, Chongqing and Tianjin, along with two medium-sized cities, Ganzhou (in Jiangxi province) and Zhenjiang (in Jiangsu province). In this year, land sale revenues significantly augmented the planned fiscal budgets of these cities, contributing an additional 74.6% for Chongqing, 20.5% for Tianjin, 85.3% for Ganzhou, and 106.1% for Zhenjiang.

The debt levels of LGFVs in these cities, expressed as a percentage of the local government's fiscal budget revenue, are notably high, reaching 915.2% for Chongqing, 785.3% for Tianjin, 909.0% for Ganzhou, and 990.3% for Zhenjiang. To assess the financial burden of this debt, we calculated the cost of debt for these LGFVs by analyzing the value-weighted average coupon rates of their outstanding bonds.[8] In 2022, the cost of debt was approximately 5% across all four cities. Based on the total LGFV debt and the calculated cost of debt for each city, our calculation reveals that the total interest payments in 2022 constituted a significant portion of these cities' fiscal budgets: 47.6% for Chongqing, 39.4% for Tianjin, 45.6% for Ganzhou, and 48.8% for Zhenjiang. This substantial financial obligation underscores the critical role of land prices in the management and sustainability of public financing, given their impact on the ability of these cities to roll over and issue new debt amidst such high levels of existing obligations.

II. Data Description

Our dataset includes detailed records of individual residential land parcel transactions across Chinese cities from 2017 to 2022, alongside aggregated data on new housing unit transactions at the city level. We have compiled data on 104,070 residential land transactions executed through the government's tender/auction/listing system across 173 cities, spanning from January 2017 to December 2022. This dataset covers all four first-tier cities, forty-five second-tier cities, with the

[8] Access to the interest rates on bank loans obtained by LGFVs is not available. Given that bond coupon rates are generally lower than the rates for bank loans, our analysis provides a conservative estimate of the interest payment burden that LGFVs might be encountering.

rest classified as third-tier cities.[9] Table A of the Appendix provides a list of these cities.

Information for each land transaction is sourced from the China Land Market website (www.landchina.com), which is operated by the Ministry of Land and Resource. The data collected for every transaction includes the location (city and district), transaction date, type, price, lot size, and the Floor Area Ratio (*FAR*), which is the ratio of the building's total floor area to the size of the land parcel. Also recorded is the land's inventory status, indicating whether it is part of an existing inventory or has been newly designated for residential use, along with a land grade that assesses its economic value on a scale from 1 to 18, where 1 represents the highest value. Furthermore, a binary variable named "*LGFV Dummy*" is used to denote whether a LGFV is the purchaser, with this specific information being derived from the Qiyeyujingtong, a widely used commercial database in the financial industry.

The transaction data for new housing units is sourced from the China Real Estate Index System (CREIS), a widely recognized commercial real estate database in China. In partnership with local governments, CREIS has collected data on transactions of new residential housing units at the city level for over two decades. This dataset, which encompasses price indices, transaction volumes, and inventory, covers the 173 cities in our sample from 2017 to 2022. CREIS's city selection criteria hinge on the availability and quality of data.

Additionally, we obtain data on local economic conditions from the Qiyeyujingtong and CSMAR database, which offers comprehensive economic, financial, and debt metrics for cities and municipalities throughout China. We compile specific variables relevant to the land and housing markets, such as the local GDP growth rate, inflation, GDP per capita, fiscal deficit rate, government tax revenue, general budget revenue (excluding revenue from land sales), fixed-asset investment, and the contribution of secondary (as well as tertiary) industries to the local GDP.

Finally, to analyze the relationship between real estate prices and firms' financing cost, we also collect data from WIND (a data vender) about all commercial paper (CP) and medium-term

[9] We follow the classification of the mainstream business magazine "China Business Network" for the first- and second-tier cities. There is broad consensus regarding the definition of these first-tier and second-tier cities; however, a uniform definition for the third- and fourth-tier cities is absent. For the sake of simplicity, we categorize all remaining cities in our sample as third-tier, acknowledging that some might be classified as fourth-tier cities in other studies.

notes (MTN) issued by nonfinancial firms in China's interbank market from 2017 to 2022. This dataset covers a wide range of bond characteristics, including coupon rate, issuance amount, maturity, and credit rating, as well as issuer characteristics, such as firm total asset, sales, ownership, leverage, and ROA.

Table 1 reports summary statistics. Panel A presents summary statistics related to the housing market. The average housing price in our dataset stands at 10781 yuan/square meter with a standard deviation of 7792 yuan/square meter.

Panel B covers residential land transactions. The data shows a notable variation in land transaction prices, with an average price of 5398 yuan/square meter and a standard deviation of 7632 yuan/square meter. Significantly, LGFVs purchase approximately 17.8% of the land parcels, highlighting their strong involvement in China's primary land market. Additionally, the primary modes of land sales are through auctions and listings, as reflected by the averages of the tender offering dummy (*Tender*) and auction dummy (*Auction*) at 0.003 and 0.297, respectively.

Panel C summarizes aggregated land market variables at the city level. Notably, residential land sales on average account for about 38.1% of local government total revenue in 2019 (*Land Dependence_2019*).[10] This highlights the pivotal role land sales play in supporting local government finance. This statistic likely underrepresents the significance of the real estate sector, as local governments also benefit from real estate taxes. There's a considerable variance in local governments' reliance on land sales. Cities at the 25th percentile exhibit a *Land Dependence_2019* of 29.4.0%, in contrast to those at the 75th percentile, which have a land dependence of 47.3%.

Panel D offers a glimpse into the economic indicators of the cities covered in our sample from 2017-2022. These cities have recorded an average annual GDP growth rate of 5.9%.

Panel E provides a summary of the 31,316 bonds covered by our bond sample. Among these bonds, 58.3% are AAA rated, 28.2% are AA+ rated, 13.5% are AA rated or below, and about 91.4% of bonds are issued by stated-owned enterprises (SOEs). The average coupon spread (relative to the treasury bond of similar maturity) is 1.32%. These characteristics are consistent with the prior

[10] Local government total revenue includes general public budget revenue, transfer income from province and central governments, governmental fund revenue (primarily land sales) and state-owned capital operation income.

literature, such as Ding, Xiong and Zhang (2022).

III. Land Transaction Price and Volume

In this section, we systematically analyze the divergence in price and volume of residential land transactions across the 173 cities, as depicted in Figure 1, by taking into account the diverse characteristics of different cities and land transactions. Our analysis focuses on a six-year sample period, encompassing three years prior to and three years following the onset of the pandemic, specifically from 2017 to 2022.

We first analyze the dynamics of land prices surrounding the onset of the Covid-19 pandemic by employing the following regression model for residential land prices at the transaction level:

$$Ln(Land\ Price)_{j,i,t} = \alpha_0 + \sum_{s=2017,t\neq2019}^{3} \alpha_s Year_{s,t} + \beta CityControls_{i,t} + \gamma ContractControls_{j,t} + Fixed\ effects + \varepsilon_{i,t}. \quad (1)$$

Here, the dependent variable represents the logarithm of the land price per square meter for each land parcel transaction *j*, in city *i* and year *t*. The year dummy variables $Year_{2017,t}$, $Year_{2018,t}$, $Year_{2020,t}$, $Year_{2021,t}$, and $Year_{2022,t}$ are assigned the value of 1, if t is equal to the corresponding years of 2017, 2018, 2020, 2021, and 2022, and 0 otherwise. The coefficients of key interest in the regression are α_s, representing the national price change in a specific year s compared to the omitted benchmark year of 2019, which is the year preceding the outbreak of Covid-19.

$CityControls_{i,t}$ represent the control variables in city *i* and year *t*, including per capita GDP (*GDP per Capita*), GDP growth rate (*GDP Growth*), fiscal deficit rate (*Fiscal Deficit*), the proportion of tax revenue in general budget revenue (*Tax Ratio*), the proportion of the secondary sector in GDP (*Secondary Sector*), and the proportion of the third sector (*Third Sector*).

We further control for transaction characteristics, $ContractControls_{j,t}$, for each land parcel *j* in year *t*. $ContractControls_{j,t}$ include the floor area ratio (*FAR*), an urban dummy variable for the land parcel to denote whether it is located in an urban area (*Urban*), a grade assigned by local governments to assess land quality (*Land Grade*) which ranges from 1 to 18 (with 1 representing the highest quality), a dummy variable indicating whether the land parcel has recently been converted into residential use (*New Land*), a dummy variable indicating whether the transaction is through a tender offer (*Tender*), and an auction dummy to signify whether the transaction is through auction (*Auction*). For detailed definitions of these variables, please refer to Appendix Table C. To address concerns regarding omitted variables, we also incorporate city fixed effects. Standard errors are clustered at the district level to account for heterogeneity within a city.[11]

We report the regression results in Table 2. It is evident that, as anticipated, land prices had an increasing trend prior to the pandemic. For example, in Column (3) with all control variables included, the coefficients on the year dummies for 2017 and 2018 are -0.211 and -0.078, respectively, suggesting substantially lower prices in these years relative to the benchmark year of 2019. An intriguing observation is made when comparing the coefficients of the year dummies for 2020, 2021, and 2022, which are 0.072, 0.152, and 0.164, respectively. These figures reveal that land prices persistently rose amidst a profound economic deceleration and contraction in demand during the Covid-19 period. Remarkably, even in 2022, which marked the third year of China's stringent zero-COVID policy and was considered the most challenging period, the land price continued to rise by 1.2% from the previous year, equating to 16.4% higher than in 2019.

The coefficients of land quality measures are all highly significant with the expected signs – lands with lower *Land Grade*, higher *FAR*, and situated in urban areas tend to have higher prices. Moreover, larger land parcels generally command higher prices, whereas parcels recently converted to residential uses—often situated in less coveted locations—typically fetch lower prices. With the inclusion of city fixed effects, the city-level control variables are mostly insignificant.[12]

We further examine the transaction volume dynamics of residential land surrounding the outbreak of the pandemic. Specifically, we employ the following city-level regression model:

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[11] There is significant heterogeneity within large Chinese cities, particularly in real estate markets. Market dynamics in city centers markedly differ from those in the outskirts. However, the robustness of our results is maintained even when errors are clustered at the city level.

[12] Without incorporating city fixed effects, certain city-level variables emerge as significant, indicating that they primarily capture variations across different cities rather than temporal changes within the same city.

$$Dep_{i,t} = \alpha_0 + \sum_{s=2017, s\neq 2019}^{3} \alpha_s Year_{s,t} + \gamma CityControls_{i,t} + Fixed\ effects + \varepsilon_{i,t} \quad (2)$$

Similar to Equation (1), the key coefficients of focus remain α_s, the coefficients of each year dummy relative to the omitted benchmark year of 2019. The $CityControls_{i,t}$ represent the same city-level control variables in Equation (1).

We use two measures of land sales volume as the dependent variable $Dep_{i,t}$ in Equation (2), specifically, the logarithm of aggregated transaction areas in hectares, *Ln(City Land Area)*, and the logarithm of total revenue in ten thousand Yuan, *Ln(City Land Value)*. As shown in Table 3 Columns (1)-(4), both the area and value from land sales consistently increased before 2020, as evidenced by the negative coefficients of the year dummies α_{2017}, α_{2018}. Even in 2020, the initial year of the pandemic, the volume of residential land sales maintained its upward trajectory. However, in 2021, the volume began to decline, with land sales plummeting in 2022.

To illustrate, consider Column (2) with all control variables included: prior to the pandemic, the area of land sales escalated by approximately 10% annually. Remarkably, land sales continued to grow by 13.7% in 2020 compared to 2019. However, in 2021, the volume reverted to 2019 levels. In 2022, the market experienced a substantial 44.9% decline in land transaction area compared to 2019, indicating an extraordinary contraction of the land market. Analogous results are apparent for the value of land sales, as highlighted in Columns (3) and (4).

Taken together, Tables 2 and 3 provide regression results that underscore a pronounced divergence between the persistent rise in land prices in 2021 and 2022 and the substantially decreased land transaction volume in 2021 and 2022. This divergence reinforces the patterns previously illustrated by Figure 1 and marks a clear departure from the typical trends observed in real estate downturns, whereby real estate prices and transaction volumes tend to decline together. Research on the U.S. housing market, including studies by Clayton, Miller, and Peng (2010), Tsai (2019), and more recently by DeFusco, Nathanson, and Zwick (2022), has highlighted a positive correlation between price and volume.[13] Similar patterns have been observed in other markets,

[13] DeFusco, Nathanson and Zwick (2022) delves into the nuanced dynamics of the lead-lag relationship between price and volume across different cities during the U.S. housing cycle in the 2000s. They found that volume drops often precede price drops during downturns, with volumes declining first while prices remain stable before eventually falling

such as the Hong Kong housing market by Ho, Ma, and Haurin (2008).

This price-volume divergence is not congruent with any factors related to land demand; oscillations in demand would typically instigate a congruent trajectory in price and transaction volume, either escalating or deescalating synchronously. Instead, the divergence between price and volume is likely propelled by supply-side factors.

An immediate argument centers on a land supply shortage. It is plausible that the constraints imposed by the Covid-19 pandemic could have impeded pre-development activities preceding land sales, such as vacating and demolishing existing structures. To probe this argument, we scrutinize the success rate of land auctions. Specifically, when a local government proffers a land parcel for sale (via tender, listing, or auction), the transaction may not culminate successfully if no suitable buyer materializes to bid a price deemed acceptable by the seller. If a supply shortage is indeed the underlying cause, one would anticipate a decline in the failure rate of land sales, attributed to the potentially unmet demand for land.

To test this hypothesis, we implement a city-level panel regression as outlined in Equation (2), deviating only in substituting transaction volume with the failure ratio as the dependent variable. We use two measures for the failure ratio. One is termed as the *Failure Ratio (piece)*, representing the proportion of unsuccessful land sales to the aggregate number of land sales endeavored in a designated city and year. The second is the *Failure Ratio (Area)*, representing the cumulative area of unsuccessful land sales relative to the entire area of proposed land sales.

As delineated in Table 4, the coefficients pertaining to the year dummies for 2021 and 2022 are uniformly positive and significant, illustrating that the years marred by the pandemic witnessed higher failure ratios compared to the years preceding it. These findings reject the hypothesis of a land supply shortage during 2021 and 2022.

The observed price-volume divergence in China's land market cannot be explained by standard real estate market frictions typically discussed in the literature. The disposition effect, as

in tandem with volumes. The dynamics observed in the Chinese land market during the Covid-19 pandemic are markedly different. Instead of experiencing delayed price drops, the market showed a persistent divergence where transaction volumes decreased while prices concurrently increased.

highlighted by Genesove and Mayer (2001), which relates to sellers' reluctance to realize losses, might explain sluggish price decreases, but not increases, during downturns. This effect is also irrelevant for local governments in China's land market, as they already own the land and are not subject to the same loss realization concerns as private sellers. Similarly, the downpayment effect proposed by Stein (1995) doesn't apply here either, since local governments don't need to purchase new land after selling. Additionally, search frictions, emphasized by Wheaton (1990) and Guren (2018), are not a factor in China's primary land market where transactions are centrally organized through listings and auctions, thereby minimizing these frictions. The extrapolative behavior of real estate buyers, explored by Glaeser and Nathanson (2017), can generate excessive price drops during downturns, but not increases. The phenomena of land hoarding and investment property purchases by speculators, as discussed by Nathanson and Zwick (2018), Gao, Sockin, and Xiong (2020), and DeFusco, Nathanson and Zwick (2022), are typically prominent during real estate booms. However, they are less likely to be a significant factor during downturns.

IV. Land Price Management by Local Governments

If neither a supply shortage nor the usual real estate market frictions can explain the divergence between the price and volume of residential land transactions during the Covid-19 period, what alternative factors might this phenomenon signify? We will now navigate towards the central theme of this paper: the management of land prices by local governments. Land serves as the key collateral enabling local governments, indirectly through LGFVs, to secure bank loans and float bonds to the public. Thus, the stabilization of land prices is imperative for local governments and affiliated entities, such as LGFVs, to roll over extant debt and secure new debt financing. Consequently, in the face of the economic frailty induced by the Covid-19 pandemic, it becomes expedient for local governments to bolster land prices by consciously curbing land supply. While this might curtail revenues from land sales, sustaining land prices would empower local governments to compensate, at least to a degree, for the diminished land sale revenue via debt financing. Maintaining land prices is also beneficial for local firms in managing their debt, which is also mostly collateralized by real estate properties.

In this section, we first adopt a difference-in-differences (DID) approach to compare land price changes during the Covid-19 period across cities with different fiscal dependence on land sales and land-based debt financing prior to the pandemic. Subsequently, we explore the methods used by local governments to manage land prices through land purchases by LGFVs.

A. Land Prices and Land-Based Public Finance

We now examine a hypothesis that cities with heightened fiscal dependence on revenues from land sales would have intensified incentives to uphold elevated land prices throughout the period of the Covid-19 pandemic. We quantify a city's fiscal dependence on land sale revenue, $Land\ Dependence\_2019_i$, as the ratio of land sales revenue to the city's total fiscal income in 2019, which includes general public budget revenue, fiscal transfer from higher-level governments, governmental fund revenue (primarily land sales revenue) and state-owned capital operation income. According to Table 1, the revenue garnered from land sales constituted 38.1% of the total revenue for local governments in our sample in 2019.

For this analysis, we regard the outbreak of the Covid-19 pandemic as an exogenous shock to the cities. Specifically, we estimate the following dynamic Difference-in-Differences (DID) model:

$$Ln(Land\ Price)_{j,i,t} = \alpha_0 + \sum_{s=2017,t\neq 2019}^{3} \alpha_s Land\ Dependence\_2019_i * Year_{s,t}$$

$$+\beta CityControls_{i,t} + \gamma ContractControls_{j,t} + Fixed\ effects + \varepsilon_{i,t} \tag{3}$$

Here, the dependent variable, $Ln(Land\ Price)_{j,i,t}$, is the logarithm of the land price (in yuan/square meter) in transaction *j*, city *i* and year *t*. We control for the same city characteristics, $CityControls_{i,t}$ and transaction characteristics $ContractControls_{j,t}$ as in Equation (1).

The estimation results are reported in Table 5, Columns (1) and (2). The insignificant coefficients of the cross terms α_{2017} and α_{2018} suggest that our setting satisfies the parallel trend assumption prior to the Covid-19 shock. More importantly, there is a larger increase in land prices during the pandemic years for cities with greater pre-pandemic fiscal dependence on land sales, as indicated by the positive and significant estimate of coefficients α_{2021} and α_{2022}. Take the estimated α_{2022} in Column (2) as an example, a one standard deviation increase in $Land\ Dependence\_2019$ is associated with a larger increase of 5.34% in land prices in the year 2022. This reveals that cities with a heightened pre-pandemic fiscal reliance on land sales tend to experience a more pronounced increase in land prices during the pandemic. The estimated coefficient α_{2022} is larger than α_{2021}, indicating that the impact of the pandemic through the fiscal pressure channel is particularly pronounced in 2022.

Beyond fiscal dependence on land sales, local governments' interventions in the land market are also directly propelled by their debt burdens. Even though the explicit, on-balance-sheet debt of local governments is closely regulated by the central government, the implicit, off-balance-sheet debt, manifested in debt assumed by LGFVs, is substantial and exhibits significant variability across cities. These LGFVs, either explicitly or implicitly backed by local governments, channel investments into local development projects. Given that LGFVs predominantly depend on debt that is collateralized by land allocated by local governments, maintaining land prices is pivotal for managing existing LGFV debt and procuring new debt. This debt burden generates direct pressure on local governments to uphold high land prices.

To delve deeper into this mechanism of debt burden, we perform a dynamic Difference-in-Differences (DID) test akin to that in Equation (3), but we substitute $Land\ Dependence\_2019$ with $LGFV\ Debt\_2019$, which represents the aggregated debt of all LGFVs in a city as a fraction of the total fiscal revenue of the city in the year 2019. A higher value of $LGFV\ Debt\_2019$ implies a greater debt pressure on local governments in the event of declining land prices.

We report the dynamic DID results in Table 5, Columns (3) and (4). The parallel trend assumption holds, as evidenced by the insignificant coefficients of the interaction terms α_{2017} and α_{2018}. The coefficients on the interaction terms between $LGFV\ Debt_{2019}$ and the year dummies for 2021 and 2022 are both positive and statistically significant. Considering Column (4), a one standard deviation increase in $LGFV\ Debt\_2019$ would entail an increase in land price of approximately 5.86% in 2022.

Taken together, Table 5 provides difference-in-differences evidence substantiating the possible endeavors of local governments to bolster land prices due to their fiscal dependence on land sales and the pressure from sustaining LGFV debt collateralized by land.

B. Land Purchases by LGFVs

How do local governments maintain high land prices? One straightforward method at their disposal is to directly curtail land supply, and it seems plausible that they have indeed reduced supply during the pandemic years. However, our analysis showcased in Table 4 reveals that the supply hasn't been reduced to a degree that would result in a decrease in the failure rate of land auctions in 2021 and 2022. In this subsection, we further elucidate an indirect mechanism employed by local governments to elevate land prices via land purchases made by LGFVs.

We hypothesize that LGFVs have been instrumental in bolstering land prices through their land purchases. Utilizing the Covid-19 outbreak as an exogenous shock, we first execute a city-level panel regression model outlined in Equation (2), incorporating *LGFV Land Ratio* (*Area*) and *LGFV Land Ratio* (*Revenue*) as the dependent variables. Here, *LGFV Land Ratio (Area)* and *LGFV Land Ratio (Value)* are construed as the proportion of lands procured by LGFVs in terms of area and value respectively, across each city and year.

Table 6, Columns (1)-(4) depict that the coefficients corresponding to the 2017 and 2018 year dummies are insignificant, indicating a stable participation of LGFVs in the land market prior to the pandemic. In stark contrast, the coefficients of the year dummies for 2020, 2021, and 2022 are all positive and statistically significant. As deduced from Column (4), the proportions of land acquired by LGFVs have seen increments of 3.6%, 6.1%, and a noteworthy 22.4% in 2020, 2021, and 2022 relative to 2019, respectively. The pronounced surge in 2022 is particularly striking. This countercyclical purchasing pattern exhibited by LGFVs underscores their proactive role in stabilizing the land market.

Beyond merely augmenting land acquisitions, it is plausible that LGFVs might also be engaged in more aggressive bidding. To explore this prospect, we apply a dynamic DID model akin to

Equation (3), but with the substitution of the independent variable, *Land Dependence_2019*, with the *LGFV Dummy*, which indicates whether a land parcel is procured by a LGFV.

In Table 7, the coefficients of primary interest are those affiliated with the cross terms between the *LGFV Dummy* and year dummies. The insignificant coefficients on *LGFV Dummy *Year 2017* and *LGFV Dummy *Year 2018* imply that the parallel trend assumption is tenable in this context.

The coefficient associated with the *LGFV Dummy* is negative and statistically significant across various specifications, which implies that, relative to other acquirers, LGFVs tend to secure land at lower prices in the reference year of 2019. Specifically, in Column (1) — without control variables — this coefficient is -0.081, while in Column (3) — encompassing all control variables — it stands at -0.089. These values correspond to substantial price reductions of 8.1% and 8.9% respectively, for land purchases by LGFVs. The interaction terms of *LGFV Dummy* with the year dummies of 2017 and 2018 are all negative, although insignificant, further reinforcing the notion that LGFVs typically settle for lower prices before the pandemic.

Intriguingly, the coefficients of the interaction terms *LGFV Dummy*Year2020* and *LGFV Dummy*Year2022* are both positive and statistically significant, suggesting that LGFVs are indeed engaged in more aggressive bidding during the Covid-19 period. Notably, the coefficient of the cross term *LGFV Dummy*Year2022* is 0.149 in Column (1), which excludes control variables, and 0.100 in Column (3), which includes them. These values indicate a relative increase of 14.9% and 10.0%, respectively, in the bidding prices of LGFVs in comparison to non-LGFV bidders in 2022. In essence, the juxtaposition of countercyclical acquisitions and bidding patterns exhibited by LGFVs underscores their pivotal role in supporting land prices during the Covid-19 period.

One might argue that during the pandemic years, LGFVs, compared to other bidders, may have acquired land of superior quality. The elevated relative bidding price of LGFVs could simply reflect the enhanced economic value of the land they procure. We consider this argument not plausible for several reasons.

Firstly, in Table 7 Column (3), we have accounted for variables typically utilized to measure land quality, including *Land Grade*, *Urban*, and *FAR*. The coefficients of these variables are all highly significant with the expected signs, as we have discussed earlier when covering regression results in Table 2. A comparison of the DID test results in Column (3) with those in Columns (1) and (2), where land quality variables are not controlled, shows the robustness of the key results associated with LGFV purchases.

Secondly, we calculate the mean of land quality measures, *Land Grade, FAR*, and *Urban*, for land parcels procured by LGFVs and non-LGFVs pre and post the onset of the pandemic and execute two-sample tests, detailed in Appendix Table D. The findings reveal no discernible trend to indicate a relative enhancement in the quality of land acquired by LGFVs post the pandemic onset. To the contrary, the land acquired by LGFVs exhibited a degradation compared to that acquired by non-LGFVs. We subsequently perform a DID test where the dependent variables are *Land Grade, Urban*, and *FAR*. The pivotal independent variable is the interaction between the *LGFV Dummy* and *Covid19*—assigned a value of 1 for the years 2020, 2021, and 2022, and 0 otherwise. These tests account for all city and transaction characteristic variables along with fixed effects. The results are reported in Appendix Table E. None of the coefficients associated with the interaction terms attain statistical significance, suggesting that post-pandemic, the lands acquired by LGFVs did not possess superior economic value compared to those acquired by non-LGFVs.

Another alternative argument for our findings in Table 7 is that LGFVs might have gained an edge over other land bidders during the unparalleled economic uncertainty brought by the Covid-19 pandemic, leading to their aggressive land bidding. Directly measuring LGFVs' information advantages is challenging, more so as China's real estate market continues to evolve in real time. Nevertheless, in an economic environment with heightened uncertainty, we expect land prices to become more sensitive to tangible fundamentals, reflected by land characteristics such as *FAR*, *Land Grade* and *Urban*. We test this hypothesis in Appendix Table F where the dependent variable is the logarithm of land price. The regression includes the city and land characteristics that we've considered in previous analyses. Our primary focus rests on the interaction terms between the year dummies (*Year2017* through *Year2022*) and the fundamental land characteristics (*FAR, Land Grade*, *Urban*). The regression results don't indicate a heightened sensitivity of land prices to these fundamental attributes during the pandemic years. Interestingly, the only significant result suggests a decreased responsiveness of land prices to the *Urban* variable.

Finally, we present additional evidence substantiating the proactive roles of LGFVs in the land market. If LGFVs are engaged in overly aggressive land acquisitions, the leverage ratio of LGFVs could experience a significant uptick during the pandemic years. This would especially be the case in a period characterized by subdued land demand.

We compute the asset-weighted average leverage of LGFVs for each city, denoted as *LGFV Leverage*, and use it as the dependent variable to conduct a panel regression specified by Equation (2), incorporating all city-level controls. This test indeed uncovers a significant increase in the leverage of LGFVs. As depicted in Table 8, Columns (1) and (2), LGFV leverage exhibited stability preceding the pandemic but began escalating from 2020 onward. To illustrate, in Column (2) with all the control variables included, the LGFV leverage in 2020, 2021, and 2022 augmented by 1.22%, 3.10%, and 4.05% compared to 2019, respectively. This increasing trend in leverage underscores the intensified and active involvement of LGFVs in the land market during the pandemic years, reflecting the aggressive land acquisitions by LGFVs.

V. Price and Volume Divergence in Housing Markets

During the Covid-19 period, there's also a notable divergence in the price and volume of housing transactions across Chinese cities, as illustrated by Panel B of Figure 1. To further elucidate this divergence, we examine the dynamics of price and sales volume of new housing units by executing a city-year panel regression as specified by Equation (2), where we incorporate the logarithm of the average new housing transaction price (in yuan/square meter) and the volume of new housing transactions as dependent variables. We use three measures of transaction volume: the number of new housing units, the aggregate area of transacted units (in square meters), and the aggregate sale revenue (in ten thousands of yuan). Our focus on new housing transactions is primarily driven by data availability. Nevertheless, it's important to note that owing to China's burgeoning urbanization, transactions of new housing units constitute the majority of housing transactions in Chinese cities (e.g., Fang et al. (2016)).

The regression results are reported in Table 9. Column (1) reveals that, as anticipated, housing prices were on a continual rise before the pandemic. For instance, the coefficients for 2017 and 2018 year dummies are -0.180 and -0.066, respectively, indicating steady price increases preceding 2020. The coefficients for 2020, 2021, and 2022 year dummies are 0.039, 0.072, and 0.071, respectively, revealing that housing prices persisted in their ascension through 2020 and 2021. Even in 2022, deemed the most challenging year, housing prices were merely 0.1% less than the preceding year and remained 7.1% above the 2019 level.

In sharp contrast to the escalation in prices, the volume of housing transactions experienced a significant contraction during the pandemic years. Columns (2)-(4) portray this, with the dependent variables being the three measures of new housing transaction volume. These volume measures sustained their growth trajectory before 2020 as marked by the negative and significant coefficients of the year dummies α_{2017}, α_{2018}. Surprisingly, even in 2020, the initial year of the pandemic, the sales of new housing units maintained a growth momentum as evidenced by the positive and significant coefficient, α_{2020}. However, 2021 marked the inception of a decline in sales volume, evident from the negative coefficient of α_{2021}. In 2022, the decline in new housing sales was markedly pronounced.

To illustrate, consider Column (3). Before the pandemic, the total area of new housing sales experienced an approximate annual increment of 9%. In 2020, sales persisted with an annual growth rate of 11.1% relative to 2019. However, 2021 saw a reversal with a decline of approximately 7.8% relative to 2019. The year 2022 witnessed a staggering 30.4% decline compared to 2019. This phenomenon of high housing prices accompanying a transaction volume slump in 2021 and 2022 mirrors the price and volume divergence in the residential land market.

Due to the lack of granular data on individual housing transactions, our capacity to analyze housing prices at the transactional level is constrained. However, our analysis shows evidence of local governments managing housing supply to support housing prices. In China, developers are required to obtain a permit prior to sell a new housing unit. This permit grants local governments a direct avenue to regulate the influx of new housing units to the market.

We examine the dynamics of the supply of new housing units by undertaking a city-year panel regression as specified in Equation (2), with the logarithm of total area (number) of new housing units approved for sales as the dependent variable. The regression results are reported in Table 10 Columns (1) and (2). Column (1) shows that, as anticipated, the new housing supply, measured by the total area, steadily ascended prior to the pandemic. Specifically, the coefficients associated with the 2017 and 2018 year dummies stand at -0.249 and -0.203, respectively. This suggests solid increases in supply before 2020. However, as the year dummies for 2020 and 2021 show, with coefficients of 0.141 and 0.110 respectively, housing supply stabilized and remained consistent with 2019 levels. Then, in 2022, there was a marked shift. The new housing supply to the market plummeted dramatically by 38.3% in comparison to 2019, indicating a significant contraction in the new housing supply for that year. In Column (2), we replace the total area of new housing permit with the total units of new housing permit and the results are consistent.

One might argue that the decline in new housing permits aligns with the diminished housing demand during the pandemic, potentially being a voluntary decision made by real estate developers. To account for this possibility, we have incorporated the contemporary transaction volume of new housing units into our regression as a control variable in Columns (1) and (2). The coefficients of the logarithm of a city's new housing transaction volume, *Ln*(*House Transaction Area*) and *Ln*(*House Transaction Units*), are positive and highly significant, indicating that new housing supply is indeed highly correlated with market demand. Nevertheless, the significant coefficient of the dummy variable *Year2022* indicates that the decline in new housing permits captured by the regressions is not due to reduction in housing demand.[14]

Alternatively, the decline in new housing permits could be driven by less housing being constructed during the pandemic. To account for this possibility, we use the logarithm of the completed new housing area, *Ln*(*Completed House Area*), and the logarithm of the area of new housing under construction, *Ln*(*Constructing House Area*), as the dependent variables in Columns (3) and (4), respectively. The results show only moderate declines of 6.7% and 6.4% in the areas

[14] Considering that the transaction volume can be affected by local government interventions in the property market, it not only serves as a control for market demand but might also attenuate the primary effect we're investigating.

of new housing completed and under construction in 2022, and these declines are not statistically significant. The sharp contrast between Columns (1)-(2) and Columns (3)-(4) indicates that the large decline in new housing permits in 2022 is not due to a lack of new housing.

Local governments have also actively intervened in the housing market to directly stabilize housing prices amid the pandemic. Based on our research from local newspapers and official government documents, we identified that more than 20 cities, during the span of 2021-2022, rolled out administrative directives to explicitly restrict real estate developers from lowering the selling prices of new housing units below set benchmarks. It's worth noting that the actual number of cities implementing such measures might be higher, as not all such directives may have been reported or documented. Details of these administrative directives can be found in Table G of the Appendix. These active interventions by local governments help to explain the observed price and volume divergence in the housing market.

IV. Potential Impacts of Managing Real Estate Prices

Managing real estate prices has significant implications for local economies, beyond how it influences debt financing of local governments. On the positive side, real estate properties are commonly used as collateral by firms to secure debt financing. Furthermore, real estate prices are important indicators for assessing the health of a local economy, influencing perceptions and decisions of firms and the public. Thus, high land prices can bolster the local economy in several ways. They enable local firms to more easily roll over existing debt and secure new debt financing at potentially lower costs. Strong land price signals may also encourage firms to increase investment, boosting economic activities.

However, there's a potential caveat to these positive effects. The public, including firms and potential lenders such as banks and bond investors, might recognize that local governments are managing real estate prices. This awareness could lead them to discount the price increases in their lending and investment decisions. Yet, such filtering of price signals may not be entirely effective due to realistic information frictions.

On the negative side, artificially boosting real estate prices negatively impacts the economy by distorting real estate transactions and preventing buyers and sellers from transacting at socially optimal levels. Buyers with genuine housing needs may be deterred by excessively high prices and decide against purchasing, leading to unmet housing demand. Moreover, real estate developers face challenges due to reduced housing transactions, which can impede their ability to sell newly built housing promptly. This delay can create significant liquidity shortages for developers, who typically operate with high leverage and depend on sales to repay their debt. The large drop in transaction volume during the pandemic has exacerbated this liquidity problem, contributing to the financial distresses faced by developers across China, including numerous delinquencies on their debt payments.

In this section, our analysis concentrates on the potential impacts of high land prices on firm financing and investment. Due to limitations in our current data set, we will not delve into the effects of local governments' management of real estate prices on household welfare and the financial health of real estate developers. Specifically, we investigate the relationship between land price and the financing cost of local firms, as well as a city's fixed-asset investment.

We face the usual endogeneity problem that the local economy determines land price together with firms' investment and financing cost. This interdependence makes it difficult to establish a clear causal relationship. Addressing this endogeneity problem fully is always challenging. In the context of our study, rather than attempting to exploit an instrumental variable which could be difficult to identify and validate, we choose a different approach. We aim to explore how the correlations between land price and local firms' investment and financing cost have evolved during the Covid-19 pandemic. The changes in these correlations may shed light on the influence of government interventions in the real estate market on local economy without directly confronting the complexities of the endogeneity problem.

We first explore the relationship between land price and the cost of finance for local firms, utilizing data from bond issuances. Our dataset encompasses all debt securities, including commercial paper (CP) and medium-term notes (MTN), issued by nonfinancial firms in China's interbank market from 2017 to 2022. This comprehensive dataset enables us to assess the cost of financing for each bond-issuing firm by examining the coupon rate of its bond issuances. As explained by Ding, Xiong and Zhang (2021), in the context of China's bond market, bonds are typically issued at par value, making the coupon rate of each bond issuance effectively represents the firm's cost of financing.

We conduct a bond-level regression analysis to explore the relationship between land prices in a city and the cost of finance for firms in the city, as measured by the coupon spread on their bond issuances. The regression is specified as follows:

$$Coupon\_Spread_{i,j,k,t} = \alpha_0 + \alpha_1 Ln(Land\ Price\_AvgQ)_{j,t-1} + \alpha_2 Ln(Land\ Price\_AvgQ)_{j,t-1} * Covid19_t + \beta CityControls_{j,t} + \gamma BondControls_{k,t} + \theta FirmControls_{i,t} + Fixed\ effects + \varepsilon_{i,j,k,t},$$

where $Coupon\_Spread_{i,j,k,t}$ denotes the coupon spread of bond *k*, issued by firm *i* in city *j* at time *t*. The coupon spread is calculated as the bond's coupon rate minus the Chinese Treasury bond yield index of a similar maturity at time *t*.

The key independent variables are the logarithm of average land transaction price in the firm's headquarter city in the quarter prior to the bond issuance date t, $Ln(Land\ Price\_AvgQ)_{j,t-1}$, and the interaction term between $Ln(Land\ Price\_AvgQ)_{j,t-1}$ and the pandemic dummy, $Covid19$, which is set to 1 for the years 2020, 2021, and 2022 (the pandemic years), and 0 otherwise. For control variables, we include standard bond characteristic variables (such as the logarithm of issuance amount, maturity, and credit rating dummies) and issuer characteristic variables, including the logarithm of total asset and sales, ownership, leverage, and ROA. Additionally, we control for economic indicators of the issuer's headquarter city, the same as those used in Table 2. The regression also includes time, firm, and bond type (CP or MTN) fixed effects.

The test results are reported in the Columns (1) and (2) of Table 11. In Column (1), the coefficient of $Ln(Land\ Price\_AvgQ)_{j,t-1}$ is negative and marginally significant, suggesting that higher land prices are associated with lower financing costs for firms. Moreover, in Column (2), we observe that this negative correlation is particularly pronounced during the pandemic period. The coefficient of the interaction term between $Ln(Land\ Price\_AvgQ)_{j,t-1}$ and $Covid19$ is negative and statistically significant, while the coefficient of $Ln(Land\ Price\_AvgQ)_{j,t-1}$ alone is not. Based on the estimated coefficients, a one-standard deviation increase in land price during the pandemic is associated with a decrease in coupon spread of 6.8 basis points for firms in the city.

The heightened correlation between land prices and firms' financing costs during the pandemic challenges the argument that the public, such as lenders, might recognize the potential management of land prices by local governments and thus rely less on land prices as an economic indicator. Instead, this trend suggests that the heightened economic uncertainty caused by the pandemic may have led lenders to depend more heavily on land prices as a critical economic indicator.[15] It is important to note, however, that our analysis does not separate the impacts caused by increased uncertainty from those resulting from the public's awareness of local governments' interventions in land pricing. Despite this, the stronger linkage between land prices and firms' financing costs provides local governments with even greater incentives to manage land prices.

We further examine the relationship between land prices and firm investments by utilizing a city-level panel regression with the following specification:

$$Ln(Fixed\ Asset\ Investment)_{j,t} = \alpha_0 + \alpha_1 Ln(Land\ Price\_AvgYear)_{j,t} + \alpha_2 Ln(Land\ Price)_{j,t} * Covid19_{j,t} + \gamma CityControls_{j,t} + Fixed\ effects + \varepsilon_{j,t}.$$

The dependent variable, $Ln(Fixed\ Asset\ Investment)_{j,t}$, is the logarithm of the fixed-asset investment in city j and year t. The key independent variables are $Ln(Land\ Price\_AvgYear)_{j,t}$, which is the logarithm of the average land transaction price in city *j* and year *t*, and the interaction term between $Ln(Land\ Price\_AvgYear)_{j,t}$ and the pandemic dummy, *Covid19*. We include the same city-level variables as controls used in previous regressions. Additionally, we include both city and year fixed effects to control for unobserved heterogeneity across cities and time.

The regression results are reported in Columns (3) and (4) of Table 11. The coefficients of $Ln(Land\ Price\_AvgYear)$ in both columns are positive and statistically significant, suggesting a positive correlation between fixed-asset investment and local land price. For instance, in Column (3), a one-standard deviation increase in $Ln(Land\ Price\_AvgYear)$ is associated with a 5.73% increase of fixed-asset investment. Moreover, in Column (4), the coefficient of the interaction term between the logarithm of land price, $Ln(Land\ Price\_AvgYear)_{j,t}$, and the pandemic dummy, *Covid19*, is also positive and marginally significant. This indicates that the relationship between land prices and city fixed-asset investments also becomes stronger during the pandemic, consistent with the heightened relationship between land prices and firms' financing costs.

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[15] Since only high-quality firms are allowed to issue bonds in China's interbank market, our analysis could underestimate the real impact of land prices on firms' cost of finance, as firms denied by the bond market would rely more on land as collateral for bank loans.

V. Conclusion and Discussions

This paper uncovers marked divergences in price and volume for residential land and property transactions across Chinese cities. Interestingly, this disparity isn't rooted in supply shortages. Instead, it stems from local governments' deliberate price management, motivated by their dependence on land sales and land-collateralized debt as fiscal financing mechanisms.

Our research sheds light on China's ongoing real estate crisis. A key concern is about excessive construction across Chinese cities, as pointed out by Glaeser et al. (2017) and Rogoff and Yang (2021, 2022). Common narratives point fingers at profit-driven real estate developers for overbuilding across Chinese cities and homebuyers who view properties more as speculative investments than as residences. While these factors undoubtedly play a role, our findings underscore a more foundational aspect of China's real estate narrative – the central role of local governments. As the primary suppliers of land, their dependence on debt secured by land value and the short-term drive to bolster their local economies also drive real estate developers towards excessive construction.

Previous research, such as Fang et al. (2016) and Glaeser et al. (2017), emphasized that home buyers' optimistic expectations have been a pivotal force behind China's real estate boom. These expectations might stem from their extrapolation of earlier economic or housing price growth trends. It's also worth noting that local governments' strong support for the real estate market has likely reinforced household confidence in engaging in housing speculation.

The deep involvement of local governments in China's real estate sector reflects the nation's distinct hybrid economic model. This system interweaves elements of free markets, honed over four decades of expansive economic reforms, with deep-rooted state planning, largely manifested through the frequent interventions of local governments and state-owned enterprises in the economy. This hybrid approach enables the state to set overarching goals, maintain social cohesion, and mitigate market-driven externalities such as pollution and systemic financial risks. Concurrently, it also allows market forces to optimize resource allocation, thereby fostering both incentives and efficiency. Market signals also help to refine state planning and provide performance measures for local governments to enhance economic efficiency, as discussed by Li and Zhou (2005) and Song and Xiong (2023).

However, this hybrid approach must also grapple with the inherent tensions between state intervention and market dynamics – market forces may also exacerbate the distortions in the state system. Our study illuminates these distortions in the real estate sector: as financial institutions extend substantial debt financing to local governments, secured against land and property values, this very financing then compels local governments to actively manage local land and housing prices, leading to significant distortions in real estate markets.

These inherent distortions present a complex backdrop to the economic challenges China confronts in addressing its real estate predicament. While bailing out distressed real estate developers might offer a short-term solution, it does not address the crux of the issue. A holistic resolution necessitates a comprehensive overhaul of local government fiscal model, specifically to diminish their heavy reliance on land sales and land-collateralized debt as primary means of local fiscal financing.

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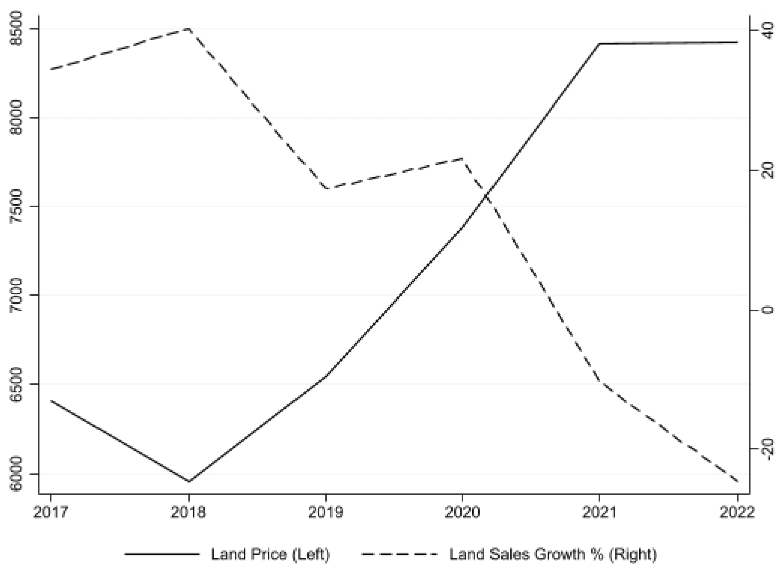
Figure 1. Price and Volume Divergence in Real Estate Markets

This figure summarizes data from 173 cities listed in Table A of the Appendix from 2017 to 2022. Panel A depicts the land price (in yuan/sqm) alongside the annual growth rate of land transaction volume (area). Panel B depicts the new housing price (in yuan/sqm) alongside the annual growth rate of new housing transaction volume (area).

Panel A: Land Price and Growth Rate of Transaction Volume



Panel B: New Housing Price and Growth Rate of Sale Volume

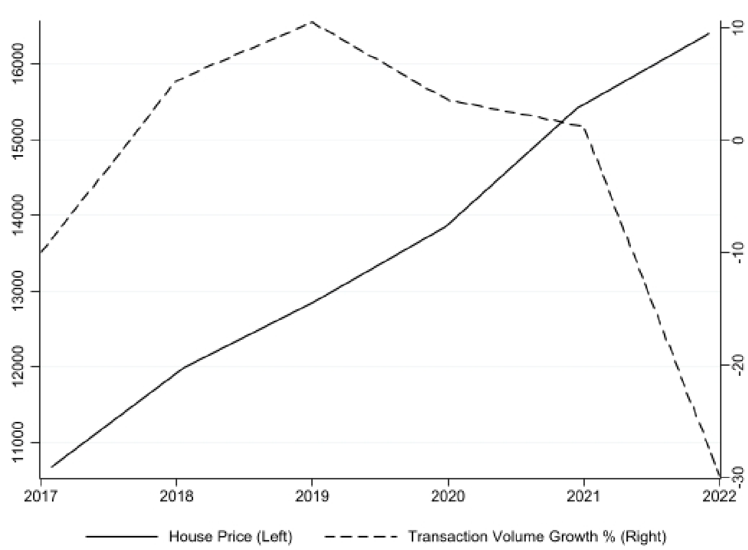


Table 1. Summary Statistics

This table shows summary statistics of the variables used in the paper. Panel A reports the characteristics of the new house market at the city level. Panel B summarizes key variables in the land market at the transaction level. Panel C presents the variables related to the land transactions at the city level. Panel D illustrates the economic indicators at the city level. The sample covers 104,070 land parcels and 968 city-year observations in 173 cities from 2017 to 2022. *Ln*(*House Price*), *Ln*(*House Transaction Value*), *Ln*(*Land Price*), and *Ln*(*City Land Value*) are all inflation-adjusted to the 2017 yuan. All variables have been winsorized at the 1st and 99th percentiles.

Variable	**N**	**Mean**	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**
Panel A: Transactions of New Housing Units at the City Level								
Ln(House Price)	849	9.125	0.476	8.577	8.781	9.022	9.366	10.054
Ln(House Transaction Units)	891	10.001	0.973	8.357	9.378	9.992	10.697	11.611
Ln(House Transaction Area)	891	14.745	0.970	13.009	14.154	14.749	15.456	16.309
Ln(House Transaction Value)	849	14.688	1.228	12.725	13.890	14.558	15.570	16.879
Ln(Completed House Area)	669	14.766	0.864	13.406	14.158	14.743	15.347	16.194
Ln(Constructing House Area)	724	17.047	0.740	15.851	16.538	17.008	17.577	18.239
Ln(Permit Area)	585	14.800	1.171	12.902	14.150	14.753	15.692	16.512
Ln(Permit Units)	584	10.010	1.275	8.024	9.393	10.014	10.939	11.770
Panel B: Residential Land Transactions at the Transaction Level								
Ln(Land Price)	104070	8.006	1.041	6.329	7.318	7.976	8.692	9.723
Ln(Land Area)	104070	1.265	0.733	0.015	0.686	1.374	1.825	2.364
LGFV Dummy	104070	0.178	0.383	0	0	0	0	1
FAR	101066	2.438	1.090	1.187	1.800	2.200	2.800	4.600
Urban	104070	0.407	0.491	0	0	0	1	1
New Land	104070	0.501	0.500	0	0	1	1	1
Land Grade	97676	5.694	4.425	1	2	4	9	14
Tender	104070	0.003	0.055	0	0	0	0	0
Auction	104070	0.298	0.458	0	0	0	1	1
Panel C: Residential Land Transactions at the City Level								
Ln(City Land Area)	1038	5.497	1.003	3.833	4.971	5.649	6.198	6.817
Ln(City Land Value)	1038	13.847	1.687	11.626	13.143	13.953	14.774	16.112
Ln(Land Price_AvgYear)	1038	8.467	0.785	7.354	7.961	8.328	8.908	9.994
Ln(Land Price_AvgQ)	4049	8.375	0.849	7.059	7.832	8.292	8.894	9.953
Failure Ratio (Area)	802	0.163	0.139	0.010	0.057	0.126	0.235	0.437
Failure Ratio (Piece)	802	0.166	0.135	0.017	0.062	0.128	0.246	0.426
LGFV Land Ratio (Area)	1032	0.182	0.172	0.000	0.042	0.135	0.278	0.538
LGFV Land Ratio (Value)	1032	0.170	0.176	0.000	0.029	0.114	0.254	0.558
LGFV Debt_2019	173	1.533	1.396	0.172	0.490	1.037	2.316	4.614
Land dependence_2019	152	0.381	0.130	0.141	0.294	0.392	0.473	0.586

Panel D: Economic Indicators at the City Level							
Ln(GDP per Capita)	1019	11.136	0.457	10.415	10.788	11.145	11.459	11.921
GDP Growth	1037	0.059	0.028	0.010	0.039	0.065	0.080	0.092
Fiscal Deficit	1035	0.095	0.068	0.015	0.045	0.083	0.124	0.215
Tax Ratio	1018	0.724	0.082	0.596	0.668	0.724	0.782	0.854
Secondary Sector	1031	0.412	0.082	0.261	0.364	0.414	0.473	0.539
Third Sector	1031	0.498	0.081	0.386	0.445	0.484	0.538	0.657
LGFV Leverage	1023	54.073	8.992	38.606	49.003	54.712	59.826	67.728
Ln(Fixed-asset Investment)	1033	7.783	0.748	6.504	7.312	7.799	8.302	9.004
Panel E: Bond Market Indicators								
Coupon Spread	31316	1.318	1.114	0.010	0.553	1.028	1.835	3.695
Ln(Issue Amount)	31316	6.702	0.720	5.670	6.215	6.802	7.090	8.006
Maturity	31316	1.591	1.670	0.164	0.493	0.740	3.000	5.000
TripleA	31316	0.583	0.493	0	0	1	1	1
DoupleAplus	31316	0.282	0.450	0	0	0	1	1
SOE	31316	0.914	0.280	0	1	1	1	1
Ln(Asset)	31300	11.458	1.273	9.543	10.533	11.337	12.301	13.674
Ln(Sales)	31195	9.702	1.871	6.777	8.216	9.655	11.188	12.714
Leverage	31300	0.642	0.122	0.416	0.575	0.654	0.723	0.832
ROA	31299	0.017	0.020	0.000	0.005	0.011	0.025	0.056

Table 2. Dynamics of Land Prices

The table reports the dynamics of the land prices in cities around the outbreak of the Covid-19 pandemic. The dependent variable is *Ln*(*Land Price*), the logarithm of the inflation-adjusted land transaction price (yuan per square meter) in the primary market. The main independent variables, Year2017 to Year2022, are year dummies. The city fixed effect is included in all the columns. The t-statistics of robust standard errors clustered at the district level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Ln(Land Price)*	(2) *Ln(Land Price)*	(3) *Ln(Land Price)*
Year2017	-0.203***	-0.224***	-0.211***
	(-7.36)	(-5.13)	(-6.08)
Year2018	-0.079***	-0.088***	-0.078***
	(-4.05)	(-4.28)	(-4.36)
Year2020	0.068***	0.105***	0.072***
	(4.05)	(3.46)	(2.92)
Year2021	0.108***	0.176***	0.152***
	(5.32)	(6.13)	(6.41)
Year2022	0.118***	0.226***	0.164***
	(5.56)	(5.30)	(4.70)
Ln(GDP per Capita)		-0.221*	-0.086
		(-1.86)	(-0.87)
GDP Growth		0.776*	0.249
		(1.68)	(0.71)
Fiscal Deficit		2.089***	1.155*
		(2.86)	(1.86)
Tax Ratio		0.398	0.336
		(1.45)	(1.57)
Secondary Sector		0.058	0.260
		(0.05)	(0.25)
Third Sector		-0.345	0.554
		(-0.26)	(0.52)
Ln(Land Area)			0.078***
			(5.75)
FAR			0.243***
			(21.41)
Urban			0.536***
			(20.15)
New Land			-0.123***
			(-9.54)
Land Grade			-0.020***
			(-7.62)
Tender			0.056
			(0.51)
Auction			0.237***
			(8.04)
Constant	8.004***	10.070***	7.423***
	(387.72)	(5.22)	(5.08)
Observations	104,065	101,539	92,438
Adjusted R-squared	0.371	0.373	0.529
City FE	YES	YES	YES

Table 3. Dynamics of Land Transaction Volume

The table reports the dynamics of the land transaction volume in cities around the outbreak of the Covid-19 pandemic. The dependent variables are *Ln*(*City Land Area*), the logarithm of the total area of land transactions in the primary market, and *Ln*(*City Land Value*), the logarithm of the inflation-adjusted total value of land transaction. The main independent variables, *Year2017* to *Year2022*, are year dummies. The city fixed effect is included in all the columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*Ln(City Land Area)*	*Ln(City Land Area)*	*Ln(City Land Value)*	*Ln(City Land Value)*
Year2017	-0.304***	-0.226***	-0.449***	-0.373***
	(-7.04)	(-3.70)	(-7.27)	(-4.22)
Year2018	-0.092***	-0.095**	-0.144***	-0.160**
	(-3.22)	(-2.28)	(-3.71)	(-2.20)
Year2020	0.136***	0.137***	0.207***	0.253***
	(4.75)	(3.02)	(5.78)	(4.52)
Year2021	-0.048	-0.018	0.045	0.139**
	(-1.24)	(-0.37)	(0.89)	(2.26)
Year2022	-0.420***	-0.449***	-0.456***	-0.364***
	(-8.67)	(-6.46)	(-7.46)	(-4.37)
Ln(GDP per Capita)		0.213		-0.164
		(0.74)		(-0.38)
GDP Growth		-0.775		0.024
		(-0.89)		(0.02)
Fiscal Deficit Rate		1.187		1.553
		(0.58)		(0.43)
Tax Ratio		1.155*		1.897***
		(1.89)		(2.69)
Secondary Sector		3.158		2.613
		(1.23)		(0.78)
Third Sector		3.523		3.933
		(1.30)		(1.09)
Constant	5.619***	-0.704	13.980***	11.253*
	(252.17)	(-0.18)	(503.50)	(1.69)
Observations	1,038	1,002	1,038	1,002
Adjusted R-squared	0.850	0.848	0.900	0.889
City FE	YES	YES	YES	YES

Table 4. Dynamics of Failure Ratio

The table reports the dynamics of the failure ratio in cities around the outbreak of the Covid-19 pandemic. The dependent variables include *Failure Ratio* (*Piece*), the ratio between the pieces of unsuccessful land sales and the total pieces of land parcels supplied in a city and year, and *Failure Ratio* (*Area*), the ratio between the total area of unsuccessful land sales and total area of lands supplied in a city and year. The main independent variables, *Year2017* to *Year2022*, are year dummies. The city fixed effect is controlled in all columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Failure Ratio* *(Piece)*	(2) *Failure Ratio* *(Piece)*	(3) *Failure Ratio* *(Area)*	(4) *Failure Ratio* *(Area)*
Year2017	-0.061***	-0.055***	-0.057***	-0.064***
	(-5.72)	(-3.28)	(-5.32)	(-3.23)
Year2018	-0.022***	-0.012	-0.000	0.005
	(-2.91)	(-1.23)	(-0.03)	(0.39)
Year2020	0.054***	0.014	0.046***	0.008
	(5.30)	(1.06)	(4.55)	(0.51)
Year2021	0.117***	0.062***	0.124***	0.081***
	(8.29)	(3.62)	(7.96)	(4.28)
Year2022	0.111***	0.035*	0.104***	0.045**
	(8.03)	(1.73)	(7.30)	(2.12)
Ln(GDP per Capita)		0.186***		0.077
		(3.51)		(1.20)
GDP Growth		-0.286		-0.349
		(-1.13)		(-1.27)
Fiscal Deficit		-0.009**		-0.011***
		(-2.30)		(-3.20)
Tax Ratio		-0.002		-0.002
		(-1.04)		(-0.83)
Secondary Sector		-3.362***		-3.404***
		(-4.24)		(-4.29)
Third Sector		-3.388***		-3.280***
		(-4.22)		(-4.09)
Constant	0.128***	1.362	0.123***	2.558***
	(19.95)	(1.58)	(17.65)	(2.90)
Observations	798	770	798	770
Adjusted R-squared	0.446	0.484	0.416	0.446
City FE	YES	YES	YES	YES

Table 5. DID Analysis of Land Price and Local Government Fiscal Conditions

The table reports the impact of local government's fiscal condition on land price. The dependent variable *Ln*(*Land Price*) denotes the logarithm of inflation-adjusted land price. The independent variable *Land Dependence_2019* is the land sales revenue divided by total fiscal revenue of a city in 2019 (total fiscal revenue = general public budget revenue + transfer income + governmental fund revenue + state-owned capital operation income). *LGFV Debt_2019* equals the aggregated LGFV liability of a city divided by the city's total fiscal revenue in 2019. *Year2017* to *Year2022* are year dummies. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. The Transaction Controls include *Ln*(*Land Area*), *FAR, Urban, New Land, Land Grade, Tender and Auction*. The city and time fixed effects are included in all columns. The *t-statistics* of robust standard errors clustered at the district level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*Ln(Land Price)*	*Ln(Land Price)*	*Ln(Land Price)*	*Ln(Land Price)*
*Land Dependence_2019*Year2017*	0.147	0.169		
	(0.75)	(0.94)		
*Land Dependence_2019*Year2018*	0.129	0.074		
	(0.80)	(0.51)		
*Land Dependence_2019*Year2020*	0.280*	0.151		
	(1.77)	(1.07)		
*Land Dependence_2019*Year2021*	0.343**	0.231		
	(2.15)	(1.60)		
*Land Dependence_2019*Year2022*	0.471***	0.411**		
	(2.71)	(2.57)		
*LGFV Debt_2019*Year2017*			0.008	0.012
			(0.36)	(0.70)
*LGFV Debt_2019*Year2018*			-0.001	-0.001
			(-0.04)	(-0.08)
*LGFV Debt_2019*Year2020*			0.017	0.018
			(1.37)	(1.60)
*LGFV Debt_2019*Year2021*			0.032*	0.035**
			(1.70)	(2.56)
*LGFV Debt_2019*Year2022*			0.040**	0.042***
			(2.29)	(2.75)
Constant	12.306***	9.129***	10.283***	7.597***
	(5.54)	(6.01)	(5.63)	(5.24)
Observations	95,063	86,444	101,539	92,438
Adjusted R-squared	0.372	0.533	0.377	0.532
City Controls	YES	YES	YES	YES
Transaction Controls	NO	YES	NO	YES
Year/Quarter FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Table 6. Land Purchases by LGFVs

The table reports the dynamics of the LGFVs' participation in the land market around the outbreak of the Covid-19 pandemic. The dependent variables *LGFV Land Ratio* (*Area*) and *LGFV Land Ratio* (*Value*) are the proportion of lands acquired by the LGFVs, measured in transaction area and value, in a given year and city. The main independent variables, *Year2017* to *Year2022*, are year dummies. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of the control variables are provided in the Appendix. The city fixed effect is included in all columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*LGFV Land Ratio (Area)*	*LGFV Land Ratio (Area)*	*LGFV Land Ratio (Value)*	*LGFV Land Ratio (Value)*
Year2017	-0.008	0.001	-0.016	0.004
	(-0.82)	(0.05)	(-1.55)	(0.28)
Year2018	-0.000	-0.002	-0.004	-0.000
	(-0.02)	(-0.17)	(-0.44)	(-0.01)
Year2020	0.026***	0.040***	0.026***	0.036**
	(2.97)	(2.72)	(2.73)	(2.43)
Year2021	0.044***	0.065***	0.042***	0.061***
	(5.00)	(5.01)	(4.49)	(4.22)
Year2022	0.180***	0.207***	0.202***	0.224***
	(13.37)	(10.87)	(13.88)	(10.56)
Constant	0.141***	-1.003	0.128***	-1.046
	(26.56)	(-1.40)	(22.12)	(-1.43)
Observations	1,032	998	1,032	998
Adjusted R-squared	0.613	0.614	0.590	0.589
City Controls	NO	YES	NO	YES
City FE	YES	YES	YES	YES

Table 7. Price of Land Purchased by LGFVs

The table reports the impact of LGFV purchase on land price. The dependent variable, *Ln*(*Land Price*), is the logarithm of the inflation-adjusted price for each land parcel (in yuan/square meters). The main independent variables include, *LGFV Dummy*, which indicates if the land is acquired by LGFVs or not, and the interaction terms between *LGFV Dummy* and year dummies, *Year2017* to *Year2022*. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of the control variables are provided in the Appendix. The city and time fixed effects are included in all columns. The *t-statistics* of robust standard errors clustered at the district level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Ln(Land Price)*	(2) *Ln(Land Price)*	(3) *Ln(Land Price)*
LGFV Dummy	-0.081**	-0.080**	-0.089**
	(-2.03)	(-2.02)	(-2.48)
*LGFV Dummy * Year2017*	-0.075	-0.076	-0.082
	(-1.31)	(-1.32)	(-1.41)
*LGFV Dummy * Year2018*	-0.004	-0.007	-0.047
	(-0.08)	(-0.12)	(-0.94)
*LGFV Dummy * Year2020*	0.075*	0.084**	0.071**
	(1.94)	(2.15)	(1.99)
*LGFV Dummy * Year2021*	0.054	0.049	0.052
	(1.15)	(1.03)	(1.30)
*LGFV Dummy * Year2022*	0.149***	0.140***	0.100**
	(3.22)	(3.01)	(2.44)
Ln(Land Area)			0.078***
			(5.89)
FAR			0.243***
			(21.44)
Urban			0.539***
			(20.42)
Land Grade			-0.121***
			(-9.39)
New Land			-0.020***
			(-7.65)
Tender			0.060
			(0.57)
Auction			0.232***
			(7.96)
Constant	8.012***	9.944***	7.315***
	(464.62)	(5.36)	(5.32)
Observations	104,065	101,539	92,438
Adjusted R-squared	0.375	0.377	0.533
City Controls	NO	YES	YES
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table 8. LGFV Leverage

The table reports the dynamics of LGFV leverage in years around the outbreak of the Covid-19 pandemic. The dependent variable *LGFV Leverage* denotes the asset-weighted average leverage ratio of LGFVs in a given city and year. The main independent variables, *Year2017* to *Year2022*, are year dummies. The City Controls include *Ln(GDP per Capita)*, *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of the control variables can be found in the Appendix. The city fixed effects are included in both columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	*LGFV Leverage* (%)	*LGFV Leverage* (%)
Year2017	-0.454	0.335
	(-1.10)	(0.53)
Year2018	-0.939***	-0.491
	(-3.76)	(-1.32)
Year2020	1.505***	1.223***
	(5.97)	(2.80)
Year2021	2.328***	3.103***
	(5.42)	(5.20)
Year2022	3.597***	4.047***
	(7.55)	(4.98)
Constant	53.063***	35.250
	(256.93)	(1.11)
Observations	1,023	987
Adjusted R-squared	0.811	0.830
City Controls	NO	YES
City FE	YES	YES

Table 9. Price and Volume of Transactions of New Housing Units

The table reports the dynamics of price and transaction volume of new housing units around the outbreak of the Covid-19 pandemic. The dependent variables include, *Ln*(*House Price*), the logarithm of the inflation-adjusted city housing price, *Ln*(*House Transaction Unit*), the logarithm of the number of new housing units transacted in a given city and year, *Ln(House Transaction Area)*, the logarithm of total transaction area of new housing units (in square meters), and *Ln*(*House Transaction Value*), the logarithm of the inflation-adjusted total transaction value (in ten thousands Yuan). The main independent variables, *Year2017* to *Year2022*, are the year dummies. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of the control variables can be found in the Appendix. The city fixed effect is included in all columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Ln(House Price)*	(2) *Ln(House Transaction Unit)*	(3) *Ln(House Transaction Area)*	(4) *Ln(House Transaction Value)*
Year2017	-0.180***	-0.150	-0.173*	-0.353***
	(-8.80)	(-1.52)	(-1.80)	(-3.93)
Year2018	-0.066***	-0.106**	-0.117**	-0.178***
	(-5.61)	(-2.15)	(-2.39)	(-3.62)
Year2020	0.039***	0.112*	0.111*	0.159***
	(3.42)	(1.89)	(1.86)	(2.64)
Year2021	0.072***	-0.078	-0.078	-0.005
	(4.69)	(-1.10)	(-1.10)	(-0.07)
Year2022	0.071***	-0.322***	-0.304***	-0.224**
	(3.29)	(-2.98)	(-2.84)	(-2.18)
Constant	8.352***	9.402**	14.759***	14.011***
	(9.49)	(1.98)	(3.13)	(3.16)
Observations	818	818	818	818
Adj. R-squared	0.960	0.781	0.782	0.872
City Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Table 10. Dynamics of New Housing Supply

This table reports the dynamics of city-level new housing supply around the outbreak of the Covid-19 pandemic. In Columns (1) and (2), the dependent variables, *Ln*(*Permit Area*) and *Ln*(*Permit Units*), denote the natural logarithm of total area and number of new housing units approved for sale by the government in a given city and year, respectively. The main independent variables, *Year2017* to *Year2022*, are year dummies. We control for *Ln*(*House Transaction Area*) and *Ln*(*House Transaction Units*), which are the natural logarithm of the area and units of new housing transactions in a given city and year. In Columns (3) and (4), the dependent variables *Ln*(*Completed House Area*) and *Ln*(*Constructing House Area*) are the logarithm of the completed area of new house construction and the area of new house under construction in a given city and year. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of these control variables can be found in the Appendix. The city fixed effect is included in all columns. The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Ln(Permit Area)*	(2) *Ln(Permit Units)*	(3) *Ln*(*Completed House Area*)	(4) *Ln*(*Constructing House Area*)
Year2017	-0.249	-0.236	0.207***	-0.098***
	(-1.29)	(-1.15)	(2.78)	(-3.61)
Year2018	-0.203*	-0.201*	-0.022	-0.085***
	(-1.80)	(-1.74)	(-0.46)	(-6.12)
Year2020	0.141	0.156	0.042	0.031
	(1.14)	(1.24)	(0.71)	(1.56)
Year2021	0.110	0.128	-0.015	0.032
	(0.88)	(0.96)	(-0.19)	(1.03)
Year2022	-0.383**	-0.412**	-0.067	-0.064
	(-1.99)	(-2.02)	(-0.67)	(-1.17)
Ln(*House Transaction Area*)	0.320**		-0.019	0.031
	(2.37)		(-0.43)	(1.30)
Ln(*House Transaction Units*)		0.331**		
		(2.32)		
Constant	-8.168	-14.465	9.218**	10.860***
	(-0.60)	(-0.96)	(2.49)	(5.72)
Observations	486	484	601	657
Adj. R-squared	0.722	0.702	0.826	0.927
City Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Table 11. Land Price, Firm Financing Cost and City Investment

The table reports the relationship between land price and the financing cost of local firms, as well as the city's fixed-asset investment. The dependent variables are *Coupon Spread,* the coupon rate minus the Chinese Treasury yield indices of similar maturity, and *Ln*(*Fixed-asset Investment*)*,* the logarithm of the fixed-asset investment of the city. The key independent variables are *Ln*(*Land Price_AvgQ*) and *Ln*(*Land Price_AvgYear*), the logarithm of the average land price in the quarter prior to the bond issuance and in the current year, respectively. *Covid19* is the dummy variable, which is equal to 1 for the years 2020, 2021, and 2022, and 0 otherwise. The City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Definitions of all control variables are provided in the Appendix. The firm, quarter and bond type fixed effects are included in Columns (1) to (2), the city and year fixed effects are included in Column (3) and (4). The *t-statistics* of robust standard errors clustered at the city level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *Coupon*	(2) *Coupon*	(3) *Ln(Fixed-asset*	(4) *Ln(Fixed-asset*
Ln(Land Price AvgQ)	-0.053*	-0.016		
	(-1.70)	(-0.45)		
*Ln(Land Price AvgQ) * Covid19*		-0.063**		
		(-2.25)		
Ln(Land Price AvgYear)			0.073**	0.065**
			(2.28)	(1.99)
*Ln(Land Price AvgYear) * Covid19*				0.026*
				(1.79)
Ln(Issue Amount)	-0.041**	-0.040**		
	(-2.45)	(-2.38)		
Maturity	-0.030**	-0.030**		
	(-2.44)	(-2.43)		
TripleA	-0.481***	-0.494***		
	(-4.45)	(-4.52)		
DoubleAplus	-0.181**	-0.193**		
	(-2.00)	(-2.10)		
SOE	-0.479***	-0.479***		
	(-5.08)	(-4.75)		
Ln(Asset)	-0.086	-0.071		
	(-0.58)	(-0.47)		
Ln(Sales)	-0.037	-0.043		
	(-1.00)	(-1.20)		
Leverage	0.616	0.573		
	(1.35)	(1.26)		
ROA	-2.086*	-2.222*		
	(-1.69)	(-1.79)		
Constant	19.134***	18.573***	-0.295	-0.240
	(2.69)	(2.64)	(-0.22)	(-0.18)
Observations	29,246	29,246	994	994
Adjusted R-squared	0.808	0.808	0.960	0.961
City Controls	YES	YES	YES	YES
Year/Quarter FE	YES	YES	YES	YES
City FE			YES	YES
Firm FE	YES	YES		
Bond Type FE	YES	YES		

Internet Appendix

Table A. The List of Cities

This table lists all of the cities covered by our sample. We categorize cities into first-tier, second-tier, and third-tier based on the classification provided by the business magazine "China Business Network", which prioritizes the magnitude of a city's economy.

First-tier			
Beijing	Shanghai	Guangzhou	Shenzhen
Second-tier			
Baoding	Changzhou	Chengdu	Dalian
Dongguan	Foshan	Fuzhou	Guiyang
Harbin	Hangzhou	Hefei	Huizhou
Jinan	Jiaxing	Jinhua	Kunming
Lanzhou	Linyi	Nanchang	Nanjing
Nanning	Nantong	Ningbo	Qingdao
Quanzhou	Xiamen	Shaoxing	Shenyang
Shijiazhuang	Suzhou	Taiyuan	Tianjin
Weifang	Wenzhou	Wuxi	Wuhan
Xi'an	Xuzhou	Yantai	Changchun
Changsha	Zhengzhou	Zhongshan	Chongqing
Zhuhai			
Third-tier			
Anqing	Anshan	Bengbu	Baotou
Baoji	Beihai	Cangzhou	Changde
Chenzhou	Chengde	Chizhou	Chuzhou
Daqing	Datong	Dandong	Deyang
Dezhou	Dongying	Ordos	Ezhou
Fangchenggang	Fuzhou	Fuyang	Ganzhou
Guilin	Haikou	Handan	Heze
Hengshui	Hengyang	Hohhot	Huzhou
Huaian	Huaibei	Huainan	Huanggang
Huangshi	Ji an	Jilin	Jining
Jiangmen	Jinzhou	Jingzhou	Jingdezhen
Jiujiang	Kaifeng	Lhasa	Langfang
Leshan	Lijiang	Lishui	Lianyungang
Liuzhou	Luan	Liupanshui	Longyan
Luzhou	Luoyang	Luohe	Maanshan
Maoming	Meishan	Meizhou	Mianyang
Mudanjiang	Nanchong	Nanping	Nanyang

Ningde	Pingdingshan	Putian	Qinhuangdao
Qingyuan	Quzhou	Rizhao	Sanming
Sanya	Shantou	Shangqiu	Shangrao
Shaoguan	Taizhou	Taian	Taizhou
Tangshan	Tianshui	Tongling	Weihai
Weinan	Urumqi	Wuhu	Xining
Xianning	Xianyang	Xiangtan	Xiangyang
Xiaogan	Xinxiang	Xinyang	Xingtai
Suqian	Suzhou	Xuchang	Yancheng
Yangzhou	Yangjiang	Yibin	Yichang
Yichun	Yinchuan	Yingtan	Yongzhou
Yueyang	Yuncheng	Zhanjiang	Zhangjiakou
Zhangzhou	Zhaoqing	Zhenjiang	Zhoushan
Zhuzhou	Zhumadian	Zibo	Zunyi

Table B. The Fiscal Budget, Land Sale Revenue, and LGFV Debt of Four Cities

This table presents data for the year 2022 on key financial metrics for Chongqing, Tianjin, Ganzhou, and Zhenjiang, including general public budget revenue, land sale revenue, total LGFV (Local Government Financing Vehicle) debt, the estimated cost of LGFV debt, and the estimated annual interest payments by LGFVs. All figures are denominated in 10 million Yuan units. The "estimated cost of debt" reflects the value-weighted average coupon rates across all outstanding bonds issued by local LGFVs. The "estimated annual interest payment" by LGFVs is calculated by multiplying the total LGFV debt by the estimated cost of this debt, providing insights into the interest obligations borne by LGFVs in these cities.

City	General public budget revenue (GPBR)	Land sales revenue	Total debt of LGFVs (as a percentage of GPBR)	Estimated cost of debt	Estimated interest payment of LGFV (as a percentage of GPBR)
Chongqing	2103.4	1561.9 (74.6%)	19249.7 (915.2%)	5.20%	1000.7 (47.6%)
Tianjin	1846.7	379.0 (20.5%)	14501.6 (785.3%)	5.02%	727.3 (39.4%)
Ganzhou	306.1	261.0 (85.3%)	2781.9 (909.0%)	5.01%	139.5 (45.6%)
Zhenjiang	343.8	364.6 (106.1%)	3405.2 (990.3%)	4.93%	167.8 (48.8%)

Table C. Variable Definitions

This table contains definitions of all the variables used in the paper.

Variable	Definition	Unit
House city-level variables		
Ln(House Price)	The logarithm of new residential house price index	Yuan/Square meter
Ln(House Transaction Units)	The logarithm of new residential houses transacted in unit	
Ln(House Transaction Area)	The logarithm of new residential houses transacted in area	Square meter
Ln(House Transaction Value)	The logarithm of new residential houses transacted in value	Ten thousand yuan
Ln(Completed House Area)	The Logarithm of completed new residential house construction area	Square meter
Ln(Constructing House Area)	The Logarithm of residential house area under construction.	Square meter
Ln(Permit Area)	The logarithm of new residential houses permitted for sales in area	Square meter
Ln(Permit Units)	The logarithm of new residential houses permitted for sales in unit	
Land transaction-level variables		
Ln(Land Price)	The natural logarithm of the land price	Yuan/Square meter
Ln(Land Area)	The natural logarithm of the land area	Hectare
LGFV Dummy	Dummy variable: 1, if the land is purchased by LGFV; 0, otherwise	
FAR	Floor area ratio: floor area/ land area	
Urban	Dummy variable: 1, if the land locates in urban districts; 0, otherwise.	
New Land	Dummy variable: 1, if the land is the newly added land; 0, otherwise. Newly added land refers to the land just transferred from agricultural or other use to residential use.	
Land Grade	Grade of the land, internal land economic value rating (from 1 to 18)	Grade 1 represents the highest quality
Tender	Dummy variable: 1, if the land is transacted through tender	
Auction	Dummy variable: 1, if the land is transacted through auction	
Land city-level variables		
Ln(City Land Area)	The natural logarithm of the total land area transacted in area	Hectare
Ln(City Land Value)	The natural logarithm of the total land transacted in value	Ten thousand yuan
Ln(Land Price_AvgYear)	The natural logarithm of the average land price in the year	Yuan/Square meter
Ln(Land Price_AvgQ)	The natural logarithm of the average land price in the quarter	Yuan/Square meter
Failure Ratio (Area)	Area of failed land sales/ area of lands supply	
Failure Ratio (Piece)	Pieces of failed land sales/ Pieces of land supply	
LGFV Land Ratio (Area)	Area of lands purchased by LGFV / Total area of lands transacted	
LGFV Land Ratio (Value)	Value of lands purchased by LGFV / Total value of lands transacted	
LGFV Leverage	Average leverage ratio of LGFV in the city	%
Land dependence_2019	Land sales revenue in 2019/Government total revenue in 2019 Government total revenue = general public budget revenue + transfer income + governmental fund revenue + state-owned capital operation income	

LGFV Debt_2019	LGFV liability in 2019/ Government total revenue in 2019 Government total revenue = general public budget revenue + transfer income + governmental fund revenue + state-owned capital operation income	
City economic indicators		
Ln(GDP per Capita)	The natural logarithm of GDP per capita	Yuan/Person
GDP Growth	GDP growth rate	
Fiscal Deficit	(Expenditure in the general public budgets - general public budget revenue)/GDP	
Tax Ratio	Tax revenue in the general public budgets/ general public budget revenue	
Secondary Sector	Proportion of secondary industry in local GDP	
Third Sector	Proportion of third industry in local GDP	
Ln(Fixed-asset Investment)	The natural logarithm of fixed-asset investment	One hundred million Yuan
Bond market indicators		
Coupon Spread	Coupon rate – the Chinese Treasury yield indices with similar maturity	%
Ln(Issue Amount)	The natural logarithm of bond issue amount	Million
Maturity	Bond maturity	Year
TripleA	Dummy variable: 1, if the bond is rated AAA; 0, otherwise	
DoupleAplus	Dummy variable: 1, if the bond is rated AA+; 0, otherwise	
SOE	Dummy variable: 1, if the bond is issued by SOE; 0, otherwise	
Ln(Asset)	The natural logarithm of the firm’s total asset	Million
Ln(Sales)	The natural logarithm of the firm’s sales	Million
Leverage	Total liability / total asset	
ROA	Return on asset	

Table D. The Quality of Land Purchased by LGFVs and Non-LGFVs

Panel A and B report the summary statistics of the quality of land acquired by non-LGFVs and LGFVs, respectively. Each panel reports the mean of *FAR*, the floor area ratio (floor area/ land area), *Land Grade*, the quality grade of the land parcel (1 for the highest quality) and *Urban*, the location dummy of the land parcel (1 for the land located in a municipal district) for two subsamples of lands acquired before and after the outbreak of Covid-19. T-test for the difference in the two samples is provided in the last column.

Panel A: Land Acquired by Non-LGFVs

	2017-2019		2020-2022			
	(1)	(2)	(3)	(4)	(4)- (2)	t-statistics
	N	Mean	N	Mean		
FAR	37449	2.576	45128	2.445	-0.131	-14.964***
Land Grade	37449	5.717	45128	5.919	0.202	5.788***
Urban	37449	0.388	45128	0.410	0.022	5.961***

Panel B: Land Acquired by LGFVs

	2017-2019		2020-2022			
	(1)	(2)	(3)	(4)	(4)- (2)	t-statistics
	N	Mean	N	Mean		
FAR	5883	2.323	8302	2.212	-0.111	-7.899***
Land Grade	5883	5.455	8302	5.779	0.324	4.810***
Urban	5883	0.497	8302	0.510	0.013	1.565

Table E. DID Analysis of Land Quality

The table reports the impact of the Covid-19 pandemic on the quality of land parcels acquired by LGFVs. The dependent variables are *FAR*, the floor area ratio (floor area/ land area), *Land Grade*, the quality grade of the land parcel (1 for the highest quality) and *Urban*, the location dummy of the land parcel (1 for the land located in a municipal district). The main independent variable is the interaction term between *LGFV Dummy,* which equals 1 if the land is acquired by a LGFV, and the pandemic dummy, Covid19, which equals 1 for lands transacted after the outbreak of the pandemic (2020-2022). The city and year/quarter fixed effect are included in all the columns. The *t-statistics* of robust standard errors clustered at the district level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
VARIABLES	Urban	FAR	Land Grade
LGFV Dummy	0.048***	-0.055*	-0.006
	(2.86)	(-1.80)	(-0.04)
LGFV Dummy * Covid19	-0.003	0.015	0.087
	(-0.19)	(0.47)	(0.61)
Ln(GDP per Capita)	-0.118**	-0.217*	0.426
	(-2.15)	(-1.77)	(0.65)
GDP Growth	0.140	0.283	-2.406
	(0.84)	(0.58)	(-0.96)
Fiscal Deficit	0.838***	-0.041	-7.769*
	(2.80)	(-0.05)	(-1.84)
Tax Ratio	-0.196*	0.083	2.250
	(-1.73)	(0.27)	(1.44)
Secondary Sector	-0.174	0.229	-0.529
	(-0.36)	(0.18)	(-0.10)
Third Sector	-0.675	-1.104	5.119
	(-1.16)	(-0.75)	(0.85)
Ln(Land Area)	0.160***	-0.338***	-0.107
	(18.75)	(-13.08)	(-1.18)
New Land	-0.057***	-0.173***	0.457***
	(-7.09)	(-8.58)	(5.49)
Tender	-0.087	0.158*	-0.620
	(-1.29)	(1.86)	(-0.66)
Auction	0.035	0.046	-0.218
	(1.52)	(1.12)	(-0.81)
Constant	1.994**	5.760***	-2.219
	(2.28)	(2.79)	(-0.26)
Observations	101,544	98,571	95,290
Adjusted R-squared	0.276	0.245	0.231
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table F. DID Analysis of Land Price and Land Characteristics

The table reports the sensitivity of land price on land characteristics. The dependent variable *Ln(Land Price)* denotes the logarithm of inflation-adjusted land price. The key independent variables include *FAR*, the floor area ratio (floor area/ land area), *Land Grade*, the quality grade of the land parcel (1 for the highest quality) and *Urban*, the location dummy of the land parcel (1 for the land located in a municipal district). *Year2017* to *Year2022* are year dummies. The City Controls include *Ln(GDP per Capita)*, *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. The city and time fixed effect are included in all columns. The *t-statistics* of robust standard errors clustered at the district level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(3)	(2)
VARIABLES	*Ln(Land Price)*	*Ln(Land Price)*	*Ln(Land Price)*
FAR * *Year2017*	0.005		
	(0.24)		
FAR * *Year2018*	-0.016		
	(-0.96)		
FAR * *Year2020*	-0.025		
	(-1.40)		
FAR * *Year2021*	-0.023		
	(-1.13)		
FAR * *Year2022*	-0.030		
	(-1.34)		
Land Grade * *Year2017*		-0.005	
		(-0.93)	
Land Grade * *Year2018*		-0.002	
		(-0.51)	
Land Grade * *Year2020*		-0.004	
		(-1.29)	
Land Grade * *Year2021*		0.001	
		(0.21)	
Land Grade * *Year2022*		-0.002	
		(-0.59)	
Urban * *Year2017*			-0.042
			(-1.03)
Urban * *Year2018*			-0.016
			(-0.49)
Urban * *Year2020*			-0.053*
			(-1.73)
Urban * *Year2021*			-0.081**
			(-2.41)
Urban * *Year2022*			-0.090**
			(-2.51)
Ln(Land Area)	0.076***	0.076***	0.076***
	(5.71)	(5.69)	(5.65)

FAR	0.256***	0.243***	0.243***
	(13.35)	(21.50)	(21.38)
Urban	0.535***	0.537***	0.582***
	(20.28)	(20.28)	(17.30)
Land Grade	-0.020***	-0.018***	-0.020***
	(-7.69)	(-4.87)	(-7.69)
New Land	-0.121***	-0.121***	-0.122***
	(-9.46)	(-9.46)	(-9.46)
Tender	0.062	0.064	0.063
	(0.58)	(0.60)	(0.59)
Auction	0.234***	0.234***	0.234***
	(8.01)	(8.06)	(8.04)
Constant	7.220***	7.286***	7.3778***
	(5.13)	(5.10)	(5.13)
Observations	92,438	92,438	92,438
Adjusted R-squared	0.532	0.532	0.532
City Controls	YES	YES	YES
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table G. Government Housing Price Control Actions

This table presents the actions of municipal governments to prevent housing price decline from local news media and government documents.

City	Province	Date	Government Action	Details
Huzhou	Zhejiang	2021/9/2	Warn on price reduction	The Huzhou Municipal Housing and Urban-Rural Development Bureau warned developers that selling commercial residential housing at prices significantly lower than the market price is risky.
Hanzhong	Shanxi	2021/12/17	Call off price reduction	The Rongsheng Binjiang Yuefu project cut the new apartment price by more than 1,000 yuan per square meter. The Housing and Urban-Rural Development Bureau suspended the sales of discounted apartments, and required the developer to return to its registered price.
Liaocheng	Shanxi	2021/11/2	Call off price reduction	The Country Garden project was ordered by the Housing and Urban-Rural Development Bureau to rectify, because the planned sales price was inconsistent with the actual sales price.
Heze	Shandong	2021/7/28	Call off price reduction	The Housing and Urban-Rural Development Bureau determined that the Evergrande project was priced far below the market price and was suspected of unfair competition.
Shenyang	Liaoning	2021/12/10	Call off price reduction	Several real estate properties in Shenyang were sold at discounted prices. The Housing Authority required developers to stop selling below the registered price.
Taizhou	Jiangsu	2021/12/30	Appeal for price stability	Taizhou Housing Association advocates "actively maintaining market stability, determining sales prices rationally, not maliciously lowering prices, and not using unfair means to compete viciously."
Yancheng	Jiangsu	2021/12/20	Regulation on price	The government agent required that actual sales price of newly built house shall not be lower than 85% of the registered price.
Zhenjiang	Jiangsu	2021/11/1	Appeal for price stability	The Zhenjiang Construction and Real Estate Association issued a “Limit Price” initiative,

				proposing that residential houses should not be sold below 85% of the registered price.
Xuzhou	Jiangsu	2021/10/3	Call off price reduction	Xuzhou Xincheng Wuyue Plaza project lowered its sales prices, and the Market Supervision Bureau ordered it to make corrections and restore the original price.
Nantong	Jiangsu	2021/9/23	Regulation on price	The Haimen District Development and Reform Commission of Nantong approved to the registration of Shangde Garden project and required that any price cut of more than 8% of the registered price must be to reported and re-approved.
Jiangyin	Jiangsu	2021/8/31	Forbid price reduction	The government is dedicated to putting an end to vicious competition. Low prices in any forms are strictly prohibited.
Zhangjiajie	Hunan	2021/12/1	Appeal for price stability	The Housing Association advocates that the sales price of residential housing should not be lower than 80% of the registered price.
Yongzhou	Hunan	2021/11/1	Warn on price reduction	Yongzhou issued the "Notice on Strictly Prohibiting Low-price Dumping". The developers were not allowed to dump at low prices for any reason to disrupt the order of the real estate market.
Zhuzhou	Hunan	2021/9/14	Call off price reduction	Several developers were selling at discounted prices. They were asked to stop price reductions immediately by the government agency.
Yueyang	Hunan	2021/8/18	Regulation on price	The transaction price of local residential housing shall not be less than 85% of the registered price.
Xiaogan	Hubei	2021/10/9	Regulation on price	For any project with sales price adjustment exceeds ±10% of the registered price, it must be re-registered.
Erzhou	Hubei	2021/9/30	Regulation on price	For any project with sales price below 90% of the registered price, it must be re-registered.
Zhangjiakou	Hebei	2021/9/26	Regulation on price	New properties shall not be sold at a price lower than 85% of the registered price
Tangshan	Hebei	2021/8/13	Call off price reduction	The municipal government warned ten developers to not maliciously lower prices.

Huizhou	Guangdong	2021/11/4	Call off price reduction	Huizhou Zhongyi and Aoyuan projects were suspended from sales and ordered to make rectifications, because their selling prices were significantly lower than the registered prices.
Tianshui	Gansu	2021/12/20	Call off price reduction	The Municipal Housing and Urban-Rural Development Bureau halted price reductions for Wanda projects, canceled online signings for contracted properties, and suspended sales of Wanda projects.
Pingtan	Fujian	2022/6/17	Regulation on price	New properties shall not be sold at a price lower than 85% of the registered price.
Anqing	Anhui	2021/10/5	Forbid price reduction	The Anqing Municipal Government held a city-wide special meeting on real estate regulation and control, requiring that sales should not be lower than the market price.