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Jeffery (Jinfan) Chang
Yuheng Wang
Wei Xiong

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ABSTRACT

During the Covid-19 pandemic (2020-2022), Chinese cities witnessed a paradox: residential land and new house prices surged while transaction volumes plummeted. We attribute this to local governments' active price management through supply controls, land acquisitions by Local Government Financing Vehicles (LGFVs), and limits on new home sales permits. Cities more dependent on land sales and land-backed debt before the pandemic experienced greater price increases and price-volume divergence, with LGFVs buying more land at higher prices than other buyers. These interventions helped sustain fiscal financing but deepened developers' financial distress, revealing unintended consequences of local governments' fiscal strategies during downturns.

Jeffery (Jinfan) Chang
The Chinese University of Hong Kong, Shenzhen (CUHK-SZ)
School of Management and Economics
Department of Finance
zhangjinfan@cuhk.edu.cn

Wei Xiong
Princeton University
Department of Economics
and NBER
wxiong@princeton.edu

Yuheng Wang
Central University of Finance and Economics
School of Finance
yuhengwang@link.cuhk.edu.cn

During the Covid-19 pandemic (2020-2022), China's real estate market showed unusual dynamics: residential land and property prices rose, while transaction volumes fell. Figure 1 illustrates this divergence using data from 173 cities, including four first-tier cities, 45 second-tier cities, and 124 smaller cities, spanning 2015 to 2022. Panel A shows residential land prices alongside the annual growth rate of land transaction volumes. Following the Covid-19 outbreak, transacted land area declined by about 10% in 2021 and 23% in 2022, while land prices continued to climb above 2019 levels.[1] Panel B reveals a similar pattern for new housing units, with prices rising even as transaction volumes dropped.[2] This divergence contrasts sharply with the synchronous movement of housing prices and transaction volumes seen in the U.S. during the Covid-19 pandemic (e.g., D'Lima, Lopez, and Pradhan, 2022).

It also contrasts with the 2006 U.S. housing downturn, where transaction volumes fell about a year before prices, a pattern DeFusco, Nathanson, and Zwick (2022) attribute to the exit of short-term speculators. Other studies point to behavioral biases among individual homeowners—the main sellers in many markets. Genesove and Mayer (2001) show that loss aversion discourages homeowners from selling during downturns. Andersen et al. (2022) and Badarinza et al. (2024) model how reference dependence and loss aversion influence seller behavior, using housing transaction data from Denmark and the U.K., respectively. Notably, Badarinza et al. (2024) find that housing prices and transaction volumes in both the U.S. and U.K. tend to move together—especially when prices decline—highlighting a sharp contrast with the price-volume divergence observed in China's real estate downturn.

More importantly, China's markets for land and new housing units are dominated by institutional, repeat sellers: local governments control land sales, and developers supply 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.

[2] We focus on the transaction prices and volume of new housing units in this paper for two reasons. First, in China's nascent real estate markets, transactions of new housing units constitute the majority of housing transactions in Chinese cities (e.g., Fang et al., 2016). Second, data for new housing units are more accessible and reliable because real estate developers in the primary markets face more stringent reporting requirements than sellers in the secondary markets.

housing. This structure limits exposure to behavioral biases such as reference dependence and extrapolative expectations. Instead, we view the divergence between prices and volume as a window into the distinct mechanisms shaping China's real estate market.

As Liu and Xiong (2020) highlight, China's real estate boom began in the late 1990s, when policy reforms made housing a tradable asset. This real estate boom played a central role in supporting urbanization in the world's most populous country, enabling the migration of hundreds of millions from rural areas to cities. The real estate sector not only provided modern housing but also helped finance urban infrastructure.

Yet concerns about the sustainability of this real estate boom long predated the Covid-19 downturn. Glaeser et al. (2017) pointed to an oversupply of vacant housing, while Rogoff and Yang (2022) warned of widespread overbuilding, especially in third-tier cities. Against this backdrop, the financial distress of major developers like Evergrande, Country Garden, and Sino-Ocean is perhaps unsurprising. More puzzling, however, is the continued rise in land and housing prices despite the mounting stress in the sector.

A key element of our analysis is the central role local governments play in China's real estate sector, stemming from their constitutional control over land. Historically unable to levy property taxes, since urban real estate was state-owned before market reforms in the 1990s and 2000s, local governments rely heavily on land sales to finance infrastructure. In 2019, land sales accounted for 38.1% of local government revenue, though this share varies widely across cities.

Beyond revenue, land also serves as collateral for borrowing through Local Government Financing Vehicles (LGFVs), which fund infrastructure and development projects. As Bai, Hsieh and Song (2016) note, to facilitate its economic stimulus post the 2008 global financial crisis, China relaxed its restrictions on local government debt financing by allowing local governments to raise debt via LGFVs, often backed by land and future land sales. As a result, falling real estate prices can directly impair their ability to roll over existing debt or raise new financing.

Given these considerations, we hypothesize that local governments—facing the economic fallout from the Covid-19 pandemic and the need to manage growing debt obligations—may have

strategically supported land prices. This behavior would be especially pronounced in cities that, prior to the pandemic, relied more heavily on land sales for revenue and on land as collateral for debt financing.

To test this hypothesis, we employ a dynamic difference-in-differences approach, comparing changes in residential land prices across cities with varying fiscal dependence on land sales and differing debt burdens. Fiscal dependence is measured by the share of land sale revenues in a city's total fiscal income in 2019, just before the pandemic. Using data from 133,971 residential land transactions across 173 cities from 2015 to 2022, we regress transaction prices on fiscal dependence, year fixed effects, their interactions, and a range of city- and parcel-level controls. Our results show that cities with higher fiscal dependence experienced significantly greater increases in land prices in 2021 and 2022 relative to 2019.

We further measure each city's debt burden as the ratio of cumulative LGFV debt to total fiscal revenue in 2019 and find a similar pattern: cities with heavier debt burdens saw higher post-pandemic land prices. Moreover, these cities exhibited greater price–volume divergence during 2020–2022, with the correlation between price and volume changes turning more negative. These findings support the view that local governments' fiscal conditions play a critical role in shaping land price dynamics in China.

Our analysis reveals an expected channel through which local governments influence land supply: land acquisitions by LGFVs. Before the pandemic, LGFVs maintained a relatively stable share of residential land purchases. However, their share rose sharply during the pandemic—from 14.1% in 2019 to 31.8% in 2022. This surge was especially pronounced in cities with greater fiscal reliance on land sales and higher levels of LGFV debt. Notably, in 2019, LGFVs paid 9.0% less than other buyers on average, but by 2022, they were paying 11.7% more. This shift toward countercyclical and higher-priced acquisitions underscores LGFVs' role in supporting land prices during the downturn. Consistent with this pattern, LGFVs' leverage increased substantially during the pandemic, reflecting their expanded land purchases.

Local governments also intervened in the housing market. In 2022, many cities, particularly

cities with greater debt burdens prior to the pandemic, reduced the issuance of permits for new housing sales, directly constraining supply. Additionally, several third-tier cities introduced administrative rules in 2021–2022 that prohibited developers from pricing new housing below government-set benchmarks, particularly in response to weak demand.

Together, these findings reveal that the price-volume divergence observed during China's real estate downturn is not merely a market anomaly but a result of active and strategic interventions by local governments. This insight is crucial for understanding the underlying mechanisms of China's real estate dynamics and assessing the sector's future trajectory.

Some commentators draw parallels between China's real estate troubles and the U.S. housing crisis of the mid-2000s. However, the two are fundamentally different. The U.S. housing bubble was primarily demand-driven, fueled by credit expansion and mortgage securitization targeting subprime borrowers (Mian and Sufi, 2009). In contrast, as noted by Xiong (2025), China's real estate boom over the past three decades has been largely supply-driven, rooted in a distinctive hybrid model. In this model, local governments finance infrastructure projects using revenue from land sales and debt backed by land. These investments, in turn, promote urban development and fuel further growth in the real estate sector—creating a tightly interwoven cycle of land, infrastructure, and housing expansion.

While this model effectively supported China's early urbanization—providing housing and infrastructure for hundreds of millions of migrants—it also incentivizes short-termist behavior. Local governments often borrow aggressively to sustain development, and even when construction booms become unsustainable, they may continue intervening to delay the inevitable downturn. Our findings reflect this pattern of short-term fiscal intervention and its impact on market dynamics.

As an integral part of the state system, the central government is widely expected to bail out any distressed local government and, by extension, may also be seen as implicitly liable for the debt of LGFVs. However, because LGFV debt lacks explicit central authorization, lender risk regulations require LGFVs to post collateral based on market values. This pressures local governments to sustain real estate prices, thereby amplifying risks to China's long-term financial

stability. Notably, while the central government is aware of these moral hazard concerns, it faces a difficult trade-off: imposing strict financial discipline to ensure long-term sustainability could trigger immediate economic distress.

Our analysis shows the complex, dual-edged effects of local government intervention on the broader economy. On the constructive side, elevated land prices helped support investment by local firms, many of which rely on real estate assets as collateral. On the destructive side, we find that real estate developers experienced sharper declines in housing sales in 2022 in cities with higher fiscal dependence on land sales. This suggests that price distortions caused by government intervention may have hindered sales, ultimately impairing developers' ability to service debt and contributing to financial distress.

To the best of our knowledge, this is the first study to identify government intervention as a key driver of real estate market dynamics—and, in particular, of the divergence between transaction volume and price during downturns.[3] The standard real estate market frictions, such as sellers' loss aversion and reference dependence (Genesove and Mayer, 2001; Andersen et al., 2022; Badarinza et al., 2024), downpayment constraints (Stein, 1995), search frictions (Wheaton, 1990; Guren, 2018), extrapolative beliefs (Glaeser and Nathanson, 2017), and speculative land hoarding or investment home purchases (Nathanson and Zwick, 2018; Gao, Sockin, and Xiong, 2020; DeFusco, Nathanson and Zwick, 2022), cannot adequately account for the price-volume divergence observed in China's real estate downturn, particularly in the primary land market. In this centralized market, the sellers—typically local governments, which constitutionally own the land—are not subject to these frictions.

Our findings shed light on the distinctive nature of China's real estate sector. Unlike in Western cities, where residential land supply is often constrained by geography and zoning (Saiz, 2010; Glaeser and Gyourko, 2018), land availability in Chinese cities is heavily influenced by the strategic behavior of a monopolistic seller—local government—whose decisions are shaped by

[3] Our analysis also contributes to the limited empirical literature on land markets by providing the first attempt to examine the joint dynamics of land prices and transaction volumes. The literature on the U.S. land market has largely focused on land prices, as seen in studies such as Albouy, Ehrlich, and Shin (2018) and David et al. (2021). An exception is Liu, Wang, and Zha (2013), who examine the joint dynamics of land prices and firm investment.

policy goals and fiscal conditions.

Our analysis also sheds light on the broader issue of high debt levels in China. While recent defaults by major developers such as Evergrande, Country Garden, and Sino-Ocean have drawn attention to financial distress in the real estate sector, our study points to a deeper underlying problem: the mounting debt burdens of local governments. This structural issue has directly influenced land and housing transaction prices and volumes, further aggravating developers' financial strain.

This insight echoes the theme in Song and Xiong (2024), who emphasize how career incentives embedded in China's GDP tournaments foster short-termism among local officials, leading to overinvestment and excessive leverage. Chang, Liu, and Yang (2024) further point out that local debt expansion is tolerated by the central government due to its choice to maintain rapid GDP growth. Importantly, our focus on institutional and fiscal dynamics contrasts with studies that highlight corruption in China's land market, such as Cai, Henderson, and Zhang (2013); Chen and Kung (2019); and Fang, Gu, and Zhou (2019).

The remainder of the article is organized as follows. Section I introduces the institutional background of China's land market and the land-based finance for local governments. Section II summarizes our data. Section III documents price and volume divergence in China's land markets. Section IV illustrates the land price management by local governments. Section V examines the price and volume divergence in housing markets. Section VI discusses the economic consequences of real estate price management. We conclude the paper in Section VII.

I. Institutional Background

Since the late 1970s, China has pursued market-oriented reforms to transform its centrally planned economy. These reforms legalized private enterprise, restructured state-owned enterprises (SOEs), and allowed market competition to expand. Today, private firms account for over 60% of GDP and more than 80% of urban employment, while SOEs have largely retreated to strategic sectors such as banking, energy, communications, and transportation. These reforms greatly

improved efficiency and propelled China to become the world's second-largest economy.

Despite market reforms, the state continues to exert strong influence through five-year plans and annual growth targets. The central government sets goals, while local governments—responsible for over 80% of fiscal spending—implement them. To fund their activities, localities rely on fiscal revenues, central transfers, and increasingly on land sales and land-backed borrowing. This section outlines China's land market and the role of land-based finance and LGFV debt in local budgets.

A. China's Land Market

All land in China is state-owned. A 1988 constitutional amendment allowed the transfer of "land use rights," laying the foundation for housing privatization. Zoning rules designate parcels for industrial, residential, or commercial purposes, and the central government sets annual caps on the amount of land that can be developed, which are then allocated across regions. Regional governments are tasked with selling land within this allocation.[4]

All transactions involving commercial and residential land are conducted using market mechanisms, including tender (招标),[5] auctions (拍卖),[6] and listings (挂牌).[7] Since the volume of secondary land transactions is minimal relative to the primary market, municipal governments dominate the land market, with the power to influence land prices by adjusting supply. Low entry barriers have drawn many firms 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

[4] 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.

[5] 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.

[6] 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.

[7] 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.

works by Chen and Kung (2019), Fang, Gu, and Zhou (2019), and Gyourko et al. (2022).

B. Land-Based Finance for Local Governments

China's 1994 tax reform shifted more revenue to the central government while leaving local spending responsibilities unchanged. To compensate, localities were granted full rights to land-sale proceeds, which soon became a core fiscal resource. By 2019, land sales accounted for 38.1% of local revenue nationwide and over 50% in some regions (Gyourko et al., 2022).[8]

Infrastructure investment has been central for local governments for two key reasons. First, rapid urbanization over the past four decades has seen hundreds of millions of people migrate from rural to urban areas, driving enormous demand for infrastructure and housing. Infrastructure not only supports urban growth but also attracts firms and migrants, directly boosting local GDP—an outcome aligned with local officials' career incentives, as shown by Li and Zhou (2005), Xu (2011), and Song and Xiong (2024).

Second, infrastructure serves as a key tool for countercyclical intervention. As discussed by Chang, Wang, and Xiong (2025), China has developed a coordinated macroeconomic framework to meet annual growth targets. When growth falls short, local governments expand infrastructure spending to fill the gap. Since 2002, infrastructure spending has exceeded 10% of GDP, reaching over 20% in 2016–2017. Without property taxes, cities have relied heavily on land sales. Unlike Western cities that fund such investments through property taxes, Chinese cities—lacking such a mechanism—rely primarily on land sales.

Local governments have relied on Urban Construction and Investment Companies—commonly known as Local Government Financing Vehicles (LGFVs)—to carry out infrastructure and development projects. These firms, owned or backed by local governments, engage in extensive debt financing with implicit government support. A single city, especially large ones, may operate dozens or even hundreds of LGFVs.

Initially, LGFVs were created to repossess land from farmers or urban residents, prepare it for development, and finance upfront costs through debt collateralized by future land-sale proceeds (Zhang and Barnett, 2014; Ambrose et al., 2015; Fang et al., 2016). Once the land was sold to developers, the proceeds repaid the debt and funded local projects.

[8] 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.

Over time, their role expanded to real estate development and commercial property operations. With government backing, LGFVs enjoy easier access to credit, making them attractive joint-venture partners for private developers. They also directly participate in land auctions—a practice examined later in this paper.

C. LGFV Debt Financing

Because budget law prohibits direct local borrowing, LGFVs provide a workaround. Their role expanded during the 2008 stimulus, when relaxed rules allowed heavy borrowing from banks and bond markets (Bai et al. 2016). Since 2011, tightening regulations have shifted financing toward shadow banking (Chen et al. 2020 and Chang et al., 2022), but borrowing has continued to rise (Chang et al., 2024).

Although local governments are not legally liable for LGFV debts, these obligations are widely regarded as off-balance-sheet public debt. When repayment difficulties arise, governments often intervene—by transferring land or arranging financing through affiliated banks and SOEs. This implicit guarantee lowers perceived risk and attracts lenders to LGFVs' high-yield instruments, though its credibility ultimately depends on local fiscal capacity and the central government's stance on discipline. As a result, lenders frequently require land or future land-sale revenues as collateral, making land prices a key determinant of borrowing capacity.

Between 2011 and 2019, stable GDP growth coincided with a sharp rise in local debt—conservatively estimated at over 14% of GDP—driven largely by pressure to meet growth targets, as shown by Chang, Wang, and Xiong (2025).

The Covid-19 pandemic intensified fiscal stress. Strict zero-Covid policies imposed heavy enforcement costs on local governments, while the 2020–2022 slowdown eroded tax revenues. Internet Appendix Table IA2 illustrates this strain for four cities in 2022: Chongqing, Tianjin, Ganzhou (Jiangxi), and Zhenjiang (Jiangsu). Land sales that year boosted planned budget revenues by 74.6%, 20.5%, 85.3%, and 106.1%, respectively. Yet LGFV debt levels were extraordinarily high, reaching 915% of fiscal revenue in Chongqing, 785% in Tianjin, 909% in Ganzhou, and 990% in Zhenjiang.[9] With average borrowing costs near 5%, interest payments alone consumed a

[9] Local governments' total fiscal revenue includes general public budget revenue, transfers from provincial and central governments, government fund revenue (primarily from land sales), and income from the operation of state-owned capital.

significant portion of general fiscal budgets: 47.6% for Chongqing, 39.4% for Tianjin, 45.6% for Ganzhou, and 48.8% for Zhenjiang.[10] These figures underscore how crucial land prices are to fiscal sustainability, given their impact on refinancing and new borrowing.

As Xiong (2025) argues, funding development through land sales can align local planning with market demand by tying revenues to long-term growth expectations. But growing reliance on LGFV debt has deepened entanglement with the real estate sector, creating incentives to prop up property prices in the short term. This dependence fueled China's real estate boom while raising questions about its long-run sustainability.

The combination of rising pre-pandemic debt, declining revenues during the pandemic, and elevated pandemic-related expenditures left local governments under severe fiscal pressure. This environment sets the stage for our analysis of their real estate activities during 2020–2022, the focus of this study.

II. Data Description

Our dataset includes detailed records of individual residential land parcel transactions across Chinese cities from 2015 to 2022, alongside aggregated data on new housing unit transactions at the city level. We have compiled data on 133,971 residential land transactions executed through the government's tender/auction/listing system across 173 cities, spanning from January 2015 to December 2022. This dataset covers all four first-tier cities, forty-five second-tier cities, with the rest classified as third-tier cities.[11] Table IA1 of the Internet 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

[10] Access to the interest rates on bank loans obtained by LGFVs is not available. We calculated the cost of debt for these LGFVs by analyzing the value-weighted average coupon rates of their outstanding bonds. As 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.

[11] 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.

for every transaction includes the location (city and district), transaction date, 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 assigned by the local governments 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 listed in Table IA1 from 2015 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), total fiscal revenue, and the contribution of secondary (as well as tertiary) industries to the local GDP.

To further analyze the relationship between real estate prices and firms' financing cost, we also collect data from WIND (a data vender) about all commercial papers (CPs) and medium-term notes (MTNs) issued by nonfinancial firms in China's interbank market. 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, state ownership, leverage, and ROA.

Finally, we acquire the detailed annual housing sales data for all publicly listed real estate developers, listed on both mainland China's A-share stock market and Hong Kong stock market,

in each city from the data vendor CREIS. We complement sales data with the balance sheet information of developers (also from the CREIS) to explore the impact of real estate price management on housing sales.

Table 1 reports summary statistics. Panel A reports summary statistics related to the housing market at the city-year level. The average logarithmic land price is 9.088, with a standard deviation of 0.479. A separate calculation indicates that the average housing price is 10221 yuan per square meter, with a standard deviation of 7416 yuan per square meter.

Panel B covers residential land transactions. The data shows a notable variation in land transaction prices, with an average logarithmic price of 7.897 and a standard deviation of 1.064. Separately, the average price is 4780 yuan per square meter, with a standard deviation of 7034 yuan per square meter. Significantly, LGFVs purchase approximately 16.8% 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 0.4% and 28.7%, respectively.

Panel C summarizes aggregated land market variables at the city and year level. Notably, residential land sales on average account for about 38.1% of local government total fiscal revenue in 2019 (*Land Dependence_2019*). 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%, 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 2015-2022. These cities have recorded an average annual GDP growth rate of 6.4%.

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

Panel F presents summary statistics of the 172 domestic real estate developers listed in mainland China's A-share stock market and the Hong Kong stock market, along with their annual sales.

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, while accounting for the heterogeneous characteristics of both cities and land transactions. Our analysis covers an eight-year period from 2015 to 2022, spanning five years before and three years after the onset of the Covid-19 pandemic.

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:

$$Ln(Land\ Price)_{i,j,t} = \alpha_0 + \sum_{s=2015,t\neq 2019}^{2022} \alpha_s Year_{s,t} + \beta CityControls_{j,t} + \gamma ContractControls_{i,t} + Fixed\ effects + \varepsilon_{i,j,t}. \quad (1)$$

Here, the dependent variable represents the logarithm of the land price per square meter for each land parcel transaction *i*, in city *j* and year *t*. The year dummy variables $Year_{2015,t}$, $Year_{2016,t}$, $Year_{2017,t}$, $Year_{2018,t}$, $Year_{2020,t}$, $Year_{2021,t}$, and $Year_{2022,t}$ are assigned the value of 1, if *t* is equal to the corresponding years of 2015, 2016, 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.

$CityControls_{j,t}$ represents the set of control variables for city *j* in year *t*, including per capita GDP (*GDP per Capita*), GDP growth rate (*GDP Growth*), fiscal deficit as a share of general budget revenue (*Fiscal Deficit*), the share of tax revenue in general budget revenue (*Tax Ratio*), and the shares of the secondary and tertiary sectors in GDP (*Secondary Sector* and *Third Sector*, respectively).

We further control for transaction characteristics, denoted as $ContractControls_{i,t}$, for each

land parcel *i* in year *t*. These controls include the floor area ratio (*FAR*); a dummy variable indicating whether the parcel is located in an urban area (*Urban*); a land quality grade assigned by local governments (*Land Grade*), ranging from 1 to 18, with 1 representing the highest quality; a dummy for newly converted residential land (*New Land*); a dummy indicating whether the transaction was conducted through a tender offer (*Tender*); and a dummy indicating whether the transaction was conducted via auction (*Auction*). Detailed definitions of these variables are provided in Appendix Table A1. To address potential omitted variable bias, we include city fixed effects. Standard errors are clustered at the district level to account for within-city heterogeneity.[12]

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 2015, 2016, 2017 and 2018 are -0.535, -0.476, -0.229 and -0.082, 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 0.054, 0.127, and 0.110, respectively. These figures reveal that land prices continued to rise despite a sharp economic slowdown and weakening demand during the Covid-19 period. Remarkably, in 2021 and 2022—the second and third years of China's stringent zero-COVID policy and arguably the most challenging phase—land prices increased by 12.7% and 11.0%, respectively, compared to 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.[13]

We further examine the dynamics of residential land transaction volumes around the onset of

[12] 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.

[13] 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.

the pandemic by estimating the following city-level regression model:

$$Dep_{j,t} = \alpha_0 + \sum_{s=2015, s\neq 2019}^{2022} \alpha_s Year_{s,t} + \gamma CityControls_{j,t} + Fixed\ effects + \varepsilon_{j,t}. \quad (2)$$

As in Equation (1), our primary interest lies in the coefficients α_s, which capture year-specific effects relative to the omitted benchmark year of 2019. The vector $CityControls_{j,t}$ includes the same city-level control variables used in Equation (1), and the city fixed effects are also included.

We use two measures of land sales volume as the dependent variable $Dep_{j,t}$ in Equation (2): the logarithm of total transacted land area in hectares, *Ln(City Land Area)*, and the logarithm of total land sales revenue in ten thousand Yuan, *Ln(City Land Value)*. As shown in Table 3, Columns (1)-(4), both land area and land value from sales steadily increased before 2020, as evidenced by the negative coefficients of the year dummies α_{2015}, α_{2016}, 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 16.8% in 2020 compared to 2019. However, in 2021, the volume reverted to 2019 levels. In 2022, the market experienced a substantial 43.1% decline in land transaction area compared to 2019, indicating an extraordinary contraction of the land market.[14] 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: land prices rose substantially in 2021 and 2022, while transaction volumes declined persistently over the same period. This divergence reinforces the patterns shown in Figure 1 and marks a clear departure from typical real estate downturns, where prices and transaction volumes usually decline in tandem.

Research on the U.S. housing market—including studies by Clayton, Miller, and Peng (2010)

[14] We also examined both the size for each land transaction and the number of land transactions using the same regression specification as in Table 3. The results, reported in Table IA3 of the Internet Appendix, show that both measures increased significantly in 2020 relative to 2019, returned to 2019 levels in 2021, and then declined sharply in 2022—mirroring the pattern observed in aggregate transaction area.

and Tsai (2019)—has documented a positive correlation between prices and transaction volumes. Similar patterns are observed in other markets, such as Hong Kong (Ho, Ma, and Haurin, 2008). Notably, Badarinza et al. (2024) find that housing prices and volumes in both the U.S. and U.K. tend to move together, particularly during price declines.

DeFusco, Nathanson, and Zwick (2022) offer a nuanced observation from the U.S. housing cycle in the 2000s, showing that transaction volumes declined roughly one year before prices, attributing the lag to the selling behavior of short-term speculators. In contrast, China's real estate downturn exhibited a much more prolonged divergence between price and volume. Crucially, the Chinese case differs structurally: the dominant role of local governments as monopolistic land sellers excludes the influence of short-term speculators, fundamentally altering the dynamics of land market adjustment.

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.

It is possible that, during the COVID-19 pandemic, logistical challenges—such as difficulties in vacating or demolishing existing structures—contributed to a reduction in land supply. Alternatively, local governments may have deliberately curtailed land supply in response to deteriorating market conditions. This reduction could have created a supply shortage, leading to falling transaction volumes alongside rising prices. To examine this possibility, we examine land supply across cities by regressing land supply—measured as either the logarithm of land supply area or the logarithm of the number of supplied parcels—on year dummies from 2015 to 2022. The results, reported in Table IA4 of the Internet Appendix, show a significant decline in land supply in 2021 and 2022.

It is difficult to determine whether the decline in land supply resulted from deliberate choices by local governments or logistical constraints imposed by the pandemic.[15] However, a supply

[15] In additional unreported analysis, we have examined whether the decline in land supply during 2021 and 2022 varied across cities with different levels of fiscal dependence on land sales and land-based debt financing prior to the

shortage alone cannot fully explain the observed dynamics. To show this, we analyze the failure rate of land auctions. Specifically, when a local government offers a parcel of land for sale, the transaction may fail if no buyer is willing to meet or exceed the government's reserve price. If the decline in volume were driven solely by a supply shortage, we would expect a lower failure rate—since tighter supply should intensify competition among buyers and increase the likelihood of successful transactions.

To test this hypothesis, we estimate a city-level panel regression following the specification in Equation (2), replacing transaction volume with the failure ratio as the dependent variable. We use two measures of the failure ratio: (1) *Failure Ratio (piece)*, defined as the fraction of unsuccessful land sales out of the total number of attempted land sales in a given city-year; and (2) *Failure Ratio (Area)*, defined as the total area of failed land sales relative to the total area of land offered.

As shown in Table 4, the coefficients on the year dummies for 2021 and 2022 are both positive and significant, indicating that land auction failure ratios were higher during the pandemic years than in the preceding period. These findings suggest that the decline in land supply alone cannot fully explain the dynamics of the land market in 2021 and 2022.

The observed price-volume divergence in China's land market cannot be explained by standard real estate market frictions commonly discussed in the literature. The disposition effect (Genesove and Mayer, 2001), which reflects sellers' reluctance to realize losses, might account for delayed price declines but cannot explain rising prices during a downturn, and is irrelevant for local governments, which already own the land and face no loss realization. The down payment effect (Stein, 1995) also doesn't apply, as local governments do not need to repurchase land. Search frictions, emphasized by Wheaton (1990) and Guren (2018), are minimized in China's primary land market, where transactions are centralized through auctions. Extrapolative expectations (Glaeser and Nathanson, 2017), may contribute to price drops during downturns, but not increases.

pandemic. The results show no significant differences across these cities. While cities with greater reliance on land sales were more exposed to the risk of falling land prices, they also had a stronger need to sustain land sale revenues. These opposing forces may have offset each other, limiting their ability to reduce land supply more than other cities.

Speculative behaviors such as land hoarding or investment-driven purchases, discussed by Nathanson and Zwick (2018), Gao, Sockin, and Xiong (2020), and DeFusco, Nathanson and Zwick (2022), are typically associated with booms and are less likely to drive market dynamics during downturns.

IV. Land Price Management by Local Governments

If supply shortages and conventional real estate market frictions cannot fully account for the divergence between land prices and transaction volumes during the Covid-19 period, what alternative factors might explain this phenomenon? We now turn to the central theme of this paper: the strategic management of land prices by local governments.

As land sales are a major source of fiscal revenue for many local governments, maintaining stable land prices is critical for fiscal sustainability. While holding prices high may temporarily suppress sales volume, allowing prices to fall risks signaling weak growth prospects, which could trigger declines in housing prices and transactions—further reducing real estate related tax revenues. Such negative signals can also erode public and investor confidence, making it harder for land prices to recover even when market conditions improve.

More importantly, land serves also as the key collateral enabling local governments, indirectly through LGFVs, to secure bank loans and float bonds to the public. Stabilizing land prices is therefore imperative for rolling over existing debt and obtaining new financing. In the face of the economic frailty induced by the Covid-19, local governments had strong incentives to support land prices by restricting land supply. While this might reduce immediate land sale revenues, maintaining high prices helps offset the shortfall through increased borrowing capacity. Stable land prices also benefit local firms, whose debts are mostly collateralized by real estate assets.

Banks and other lenders may find it difficult to fully adjust their lending practices to account for government-managed land prices, due to two key factors. First, political pressure: China's financial system operates under explicit and implicit directives to support the state—including local governments—especially during periods of fiscal stress. While loan officers may recognize

price distortions, banks' risk compliance primarily relies on collateral values, which are typically based on prevailing market prices. Second, information frictions: the heightened uncertainty during the pandemic made it difficult for financial institutions to gauge the extent of price distortions, limiting their ability to adjust lending accordingly.

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, $Land\ Dependence_2019_j$, as the ratio of land sales revenue to the city's total fiscal revenue 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.

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:

$$Ln(Land\ Price)_{i,j,t} = \alpha_0 + \sum_{s=2015, t\neq 2019}^{2022} \alpha_s Land\ Dependence_2019_j * Year_{s,t} + \beta CityControls_{j,t} + \gamma ContractControls_{i,t} + Fixed\ effects + \varepsilon_{i,t} \quad (3)$$

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

The estimation results are reported in Table 5, Columns (1) and (2). The insignificant coefficients of the cross terms α_{2015}, α_{2016}, 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 4.80% 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_{2015},

α_{2016}, 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 6.00% in 2022.

In Column (5), we include interaction terms between the year dummies and both $Land\ Dependence_2019$ and $LGFV\ Debt_2019$. Notably, the interaction terms between $LGFV\ Debt_{2019}$ and the year dummies for 2021 and 2022 remain highly significant, with only modest reductions in magnitude relative to Column (4). In contrast, the interaction term between $Land\ Dependence_2019$ and the 2022 year dummy shows a more substantial decline compared to Column (2) and becomes only marginally significant. These results suggest that debt financing exerts a stronger influence than land sale revenues in pressuring local governments to sustain land prices.

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.[16]

We further examine the divergence between land prices and transaction across cities with varying fiscal dependence on land sales. Specifically, we use two measures, the *Land Area Growth Rate*, defined as the annual growth rate of aggregated land transaction area in each city, and the *Land Price Growth Rate*, defined as the annual growth rate of the transaction-area-weighted average land price in each city. We regress the *Land Price Growth Rate* on *Land Area Growth Rate*, and the interaction term between *Land Area Growth Rate* and *Covid19*, a dummy (equal to 1 for 2020–2022 and 0 otherwise). The regression also controls for the same city characteristics as in Table 5, together with city and year fixed effects.

The results, reported in Table 6 Column (1), show that the coefficient on *Land Area Growth*

[16] In unreported analysis, we test the robustness of our difference-in-differences results to the linearity assumption by dividing cities into three or four groups based on their 2019 levels of *Land Dependence* or *LGFV Debt*, and comparing land prices across these groups each year using 2019 as the baseline. The results show that only cities in the highest group experienced large and statistically significant price increases in 2021 and 2022, while effects for other groups are generally insignificant—supporting our main findings and revealing non-linearity in the relationship.

Rate, $\alpha_1 = 0.034$, is close to zero and statistically insignificant, indicating no systematic correlation between price and volume before the pandemics, By contrast, the coefficient on the interaction term, $\alpha_2 = -0.145$, is negative and statistically significant. Moreover, the sum of the two coefficients, $\alpha_1 + \alpha_2$, is both negative and statistically significant (F-value=8.59), suggesting a strong negative correlation between land prices and transaction volumes during the Covid-19 period. Taken together, these results provide evidence of a pronounced price–volume divergence across cities during the pandemic.

To examine heterogeneity across cities, we divide the sample cities into three groups based on either *Land Dependence_2019* or *LGFV Debt_2019*, and re-estimate the regressions separately within each group. Columns (2)–(4) report results for the Land Dependence–sorted groups, while Columns (5)–(7) correspond to the LGFV Debt–sorted groups. Across all specifications, the coefficients on the interaction terms are negative, but statistical significance emerges only in the high-LGFV-debt group. The F test for $\alpha_1 + \alpha_2$ is also significant for this group (F-value=9.14). These findings suggest that cities with higher debt burdens are more inclined to support land prices, thereby exhibiting stronger price-volume divergence. This pattern reinforces the notion that debt financing places greater pressure on local governments to stabilize land prices than reliance on land-sale revenues alone.

B. Land Purchases by LGFVs

How did local governments maintain high land prices? One possibility is that they reduced supply during the pandemic. While this may have played a role, our analysis in Table 4 reveals that land supply was not reduced to an extent that would lower the failure rate of land auctions in 2021 and 2022. This suggests that additional mechanisms were at work. In this subsection, we examine one such mechanism: the use of LGFVs by local governments to support land prices through direct land purchases.

As shown in the summary statistics in Table 1, LGFVs accounted for 16.8% of land transactions by area and 15.9% by value in our sample. Beyond infrastructure development, LGFVs may also participate in real estate projects—either as independent developers or in

partnership with private firms. In such cases, LGFVs directly compete in land auctions for real estate development.

During the Covid-19 period, amid a real estate downturn, media reports suggest that some land acquired by LGFVs remained undeveloped for extended periods. In these cases, LGFVs used the acquired land as collateral to borrow and pay the bidding prices to local governments, even when market conditions did not justify immediate development. These transactions helped support land prices and, in effect, enabled local governments to borrow off-balance-sheet through LGFVs.[17]

We hypothesize that LGFVs played a key role in propping up land prices through their land purchases. Using the Covid-19 outbreak as an exogenous shock, we estimate a city-level panel regression based on Equation (2), with *LGFV Land Ratio* (*Area*) and *LGFV Land Ratio* (*Revenue*) as dependent variables. These variables capture the share of land purchased by LGFVs in each city and year, measured by area and transaction value, respectively. The results are presented in Table 7: Panel A uses *LGFV Land Ratio* (*Area*), and Panel B uses *LGFV Land Ratio* (*Value*). Both panels show highly consistent patterns.

In Panel A, Column (1) shows that the coefficients for the year dummies for 2015–2018 are statistically insignificant, suggesting stable LGFV participation in the land market before the pandemic. By contrast, the coefficients for 2020, 2021, and 2022 are all positive and statistically significant, indicating increases of 3.3%, 6.0%, and a striking 19.5% in LGFV land purchases relative to the LGFV purchase of only 14.1% in 2019. The sharp rise in 2022 highlights a strongly countercyclical purchasing pattern, underscoring LGFVs' active role in stabilizing the land market.

To examine heterogeneity across cities, we divide the sample cities into three groups based on either *Land Dependence_2019* or *LGFV Debt_2019*, and run the regressions separately within each group. Columns (2)–(4) report results for groups sorted by *Land Dependence_2019*, while Columns (5)-(7) for groups sorted by *LGFV Debt_2019*. The findings show that cities in the

[17] In the post-pandemic period, the central government introduced policies allowing cities to support the real estate sector by issuing official municipal bonds, which carry significantly lower interest rates than LGFV debt. Some cities have used the proceeds from these bonds to buy back undeveloped land from LGFVs—effectively replacing high-cost LGFV debt with lower-cost official debt.

highest-dependence groups experienced significantly larger increases in LGFV land purchases in 2021 and 2022, consistent with stronger incentives to support land prices in cities with stronger fiscal dependence on land sales or land-based debt financing. Panel B demonstrates very similar pattern.

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 at the transaction level 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 8, the coefficient associated with the *LGFV Dummy* is negative and statistically significant across various specifications, which implies that, relative to other acquirers, LGFVs tended to secure land at lower prices in the reference year of 2019. Specifically, in Column (1)—without control variables—this coefficient is -0.082, while in Column (3)—encompassing all control variables—it stands at -0.090. These values correspond to substantial price reductions of 8.2% and 9.0% respectively, for land purchases by LGFVs. The coefficients of primary interest are those affiliated with the cross terms between the *LGFV Dummy* and year dummies. The interaction terms of *LGFV Dummy* with the year dummies of 2016, 2017 and 2018 are all insignificant, indicating no evident differences in the prices paid by LGFVs in these pre-pandemic years from other bidders.[18]

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 0.157 in Column (1), which excludes control variables, and 0.117 in Column (3), which includes them. These values indicate a relative increase of 15.7% and 11.7%, respectively, in the bidding prices of LGFVs in comparison to non-LGFV bidders in 2022.

[18] Note that the interaction term between the *LGFV Dummy* and the 2015 year dummy is positive and highly significant, indicating that LGFVs placed more aggressive bids than other buyers in 2015—a year marked by significant distress in China's real estate market.

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 8 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 the Internet Appendix Table IA5. 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 Internet Appendix Table IA6. 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 8 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 Internet Appendix Table IA7 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 (*Year2015* 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 in a panel regression based on Equation (2), including all city-level controls. The results reveal a significant rise in LGFV leverage during the pandemic. As shown in Table 9, leverage remained stable before 2020 but began to increase thereafter, rising by 0.86% in 2020, 3.69% in 2021, and 4.06% in 2022 relative to 2019. This upward trend underscores the intensified and proactive role of LGFVs in the land market during the pandemic, reflecting their aggressive land acquisitions.

Taken together, our analysis in this section shows that cities with greater fiscal dependence on land sales before the onset of the pandemic experienced greater residential land price increases during the pandemic and that LGFVs purchased more land at higher prices than non-LGFVs during the pandemic. These findings support our hypothesis that local governments actively managed

land prices during the pandemic, consistent with their incentives to support their own debt financing.

V. Price and Volume Divergence in Housing Markets

During the Covid-19 period, a notable divergence emerged between housing prices and transaction volumes in new housing markets across Chinese cities, as shown in Panel B of Figure 1. To further examine this divergence, we conduct a city-year panel regression based on Equation (2), using the logarithm of the average new housing transaction price (in yuan per square meter) and measures of transaction volume as dependent variables. Specifically, we consider three volume measures: the number of new housing units sold, the total transacted new housing floor area (in square meters), and total new housing sales revenue (in ten thousand yuan).

Our focus on new housing transactions is driven primarily by data availability. Nevertheless, it is worth noting that owing to China's burgeoning urbanization, new housing account for the majority of housing transactions in Chinese cities (e.g., Fang et al., 2016). In 2023, new housing sales represented 62.9% of all housing transactions nationwide.[19] Accordingly, the official housing price index published by the National Bureau of Statistics of China is also based on new home transactions. As a result, new home prices serve as a critical barometer of local economic performance and play a central role in shaping banks' and investors' financing decisions for local governments and firms, thereby giving local governments strong incentives to manage them.

The regression results are reported in Table 10. Column (1) shows that housing prices continued to rise before the pandemic, with the year dummies for 2017 and 2018 at -0.21 and -0.072, respectively, relative to the 2019 baseline. The coefficients for 2020, 2021, and 2022 are 0.030, 0.059, and 0.054, indicating that housing prices continued to climb through 2020 and 2021. Even in 2022—the most challenging year—remained flat from 2021 and 5.4% above 2019 levels.

In sharp contrast to the continued rise in prices, the volume of housing transactions contracted significantly during the pandemic years. Columns (2)-(4) of Table 10 present results using the three measures of new housing transaction volume as dependent variables. These measures show steady growth before 2020, as indicated by the negative and significant coefficients on the year dummies

[19] See report by the CCTV: https://m.huanqiu.com/article/4Fjv5oxTt9z

α_{2017} and α_{2018}. This growth slowed in 2020, the initial year of the pandemic, but sales volume still showed a positive, albeit insignificant, coefficient for α_{2020}. The decline began in 2021, as reflected in the negative coefficient for α_{2021}, and became markedly more severe in 2022.[20] Using Column (3) as an example, transaction volume fell by approximately 11.5% in 2021 and by a striking 39.4% in 2022, both relative to 2019.

Taken together, Table 10 confirms that high housing prices coincided with a sharp decline in transaction volume in 2021 and 2022, echoing the price-volume divergence observed in the residential land market. While local governments do not directly purchase homes, they can regulate new housing supply by controlling the issuance of sales permits.

Unlike in many countries where homes can be sold only upon completion, China allows developers to sell new homes before construction is finished. Developers may apply for sales permits once construction reaches a certain stage—such as the completion of a specified portion of the above-ground structure or roof sealing—though the specific threshold varies by city. These unfinished units are sold through forward contracts, allowing developers to collect initial payments at contract signing and additional payments as construction progresses. As a result, developers have little incentive to delay permit applications, even under market uncertainty. Homebuyers can also use these contracts to obtain mortgage financing from banks. This forward-sale model is widely adopted across Chinese cities, and anecdotal evidence suggests that unfinished units account for up to 80% of new home sales, although systematic data is lacking.

We examine the joint dynamics of new home prices and sales permits using the DID specification in Equation (3). Table 11 reports the regression results: Columns (1) uses the logarithm of the inflation-adjusted housing price in a given city and year as the dependent variable, while Columns (2) and (3) use the logarithm of the total area and number of new housing units approved for sale, respectively. The data do not distinguish between permits for finished or unfinished units. Our main explanatory variable, *LGFV Debt_2019*, is the ratio of a city's

[20] Columns (2) and (3) also show positive but insignificant coefficients for 2015 and 2016, reflecting declines in transaction volume during those years. This drop was driven by central government policies aimed at curbing speculative housing purchases.

aggregated LGFV liabilities to its total fiscal revenue in 2019, capturing the city's debt burden. Control variables include the lagged logarithms of housing transactions, *Ln(House Transaction Area t-1)* and *Ln(House Transaction Units t-1)*, and logarithms of housing price, *Ln(House Price)*, as well as the same set of city characteristics used in earlier regressions. All regressions include both city and year fixed effects.

The results in Table 11 indicate that cities with heavier debt burdens in 2019 experienced significantly larger increases in new housing prices during 2021–2022. In contrast, these cities issued significantly fewer new home sales permits in 2022, measured both by total area and by number of units. This sharp divergence between rising prices and declining permit issuance highlights how highly indebted cities curtailed new supply as a means of supporting housing prices during the pandemic. It mirrors our land market finding that local governments deliberately restricted land supply to sustain prices during the Covid period.

In addition, local governments also intervened directly to stabilize housing prices during the pandemic. Based on reviews of local newspapers and official documents, we identify over 20 cities that issued administrative directives between 2021 and 2022, explicitely prohibiting developers from lowering the selling prices of new housing units below set benchmarks. The true number may be higher, as not all such directives are publicly disclosed. Details of these administrative directives are provided in Table IA8 of the Internet Appendix. These coordinated interventions can help explain the persistent divergence between prices and transaction volumes in the new housing market.

VI. Potential Impacts of Managing Real Estate Prices

Managing real estate prices carries broader economic implications beyond supporting local government debt financing. As integral parts of the state apparatus, local governments are widely perceived as entities the central government would rescue in times of distress—a perception that extends to LGFVs, making them more attractive to lenders. However, because LGFV debt lacks explicit central authorization, lender risk regulations often require LGFVs to post collateral based on market values. This, in turn, pressures local governments to sustain real estate prices,

amplifying long-term financial stability risks.

While the central government is aware of these moral hazard concerns, it faces a difficult trade-off: imposing strict financial discipline could undermine short-term economic stability. As argued by Chang, Liu, and Yang (2024), the central government's tolerance of local debt expansion through shadow banking reflects a strategic choice— driven in part by the pressure to meet national growth targets. Although the development of shadow banking has been influenced by regulatory arbitrage, it is ultimately the result of the central government's tacit approval for the sake of maintaining targeted national economic growth.

Managing real estate prices also has significant implications for local economies. On the positive side, real estate assets are commonly used as collateral, enabling firms to secure debt financing. High land prices can help local firms roll over existing debt and secure new financing, potentially at lower costs. Furthermore, real estate prices serve as signals of economic vitality, shaping the expectations and decisions of firms and the public. Strong land prices may therefore encourage greater investment and stimulate local economic activity.[21]

On the negative side, artificially boosting real estate prices distorts market activity by preventing transactions at socially optimal levels. Buyers with genuine housing needs may be priced out, leading to unmet housing demand. At the same time, developers face reduced housing transactions, making it harder to sell newly built units. This creates liquidity pressures, particularly for highly leveraged developers who rely on sales revenue to service their debt. The sharp drop in transaction volume during the pandemic exacerbated these pressures, contributing to widespread financial distress and a surge in debt delinquencies among developers across China.

In this section, we examine two potential consequences of real estate price management: its impact on firm financing, and its effect on developers' housing sales.

A. Firm Financing

We begin by investigating the relationship between land prices and the financing costs of local firms. A key challenge is endogeneity: land prices and financing costs are jointly determined by local economic conditions, making causal inference difficult. Rather than relying on an

[21] 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.

instrumental variable, which is often difficult to identify and validate, we take a different approach. We focus on how the correlation between land prices and firm financing costs changed during the Covid-19 pandemic. The shift offers insight into how government intervention in the real estate market may have influenced local economic conditions.

We use bond issuance data from local firms to assess financing costs. The dataset includes all commercial papers (CPs) and medium-term notes (MTNs) issued by nonfinancial firms in China's interbank market from 2017 to 2022, covering 29,246 issuances. Financing cost is measured by the coupon rate of each debt security. As noted by Ding, Xiong and Zhang (2022), bonds in China are typically issued at par, so the coupon rate effectively reflects the firm's cost of financing.

We conduct a bond-level regression to explore the relationship between city-level land prices and firm financing costs, as measured by the coupon spread on bond issuances. The regression is specified as follows:

$$Coupon_{Spread_{i,j,k,t}} = \alpha_0 + \alpha_1 Ln\left(Land\ Price_{AvgQ}\right)_{j,t-1} + \alpha_2 Ln\left(Land\ Price_{AvgQ}\right)_{j,t-1} * Covid19_t$$
$$+\beta CityControls_{j,t} + \gamma BondControls_{k,t} + \theta FirmControls_{i,t} + Fixed\ effects + \varepsilon_{i,j,k,t}. \quad (4)$$

Here, $Coupon_Spread_{i,j,k,t}$ is the coupon rate of bond k, issued by firm i in city j at time t, minus the Chinese Treasury bond yield index of a similar maturity. The key explanatory variable is the logarithm of the average land transaction price in the firm's headquarter city in the previous quarter, $Ln(Land\ Price_AvgQ)_{j,t-1}$, along with its interaction with a pandemic dummy, $Covid19$, which equals 1 for the years 2020-2022 and 0 otherwise.

We include standard control variables: bond characteristics (the logarithm of issuance amount, maturity, and credit rating) firm characteristics (the logarithm of total asset and sales, ownership type, leverage, and ROA), city-level economic indicators (as in Table 2). The regression also incorporates time, firm, and bond-type (CP or MTN) fixed effects.

Results are reported in Table 12. Column (1) shows that $Ln(Land\ Price_AvgQ)_{j,t-1}$ is negatively associated with coupon spreads, though only marginally significant. Column (2) reveals that this negative relationship strengthens during the pandemic: the interaction term is negative and statistically significant, while the standalone effect of land price becomes insignificant. A one-standard deviation increase in land price during the pandemic is associated with a 6.8 basis point

reduction in the coupon spread.

The heightened correlation during the pandemic challenges the argument that lenders discount land prices due to potential price manipulation by local governments. Instead, it suggests that under increased economic uncertainty, lenders may have relied more heavily on land prices as an indicator for local economic strength.[22]

We further split the sample into LGFV firms—those affiliated with local governments—and non-LGFV firms. During the sample period, LGFVs issued 10,225 bonds, while non-LGFVs issued 19,002. Columns (3) and (4) of Table 11 report the regression results separately for each group. Notably, the bond spread of non-LGFV firms is negatively and significantly correlated with the interaction term between $Ln(Land\ Price_AvgQ)_{j,t-1}$ and the $Covid19$ dummy, while this relationship is not observed for LGFV firms. This contrast suggests that financing costs for non-LGFVs are more sensitive to local real estate prices.

Although LGFVs need to post land and real estate assets as collateral to roll over debt, their financing costs are largely insulated from market fluctuations due to implicit government guarantees. In contrast, non-LGFVs, lacking such guarantees, are more exposed to real estate price changes. The stronger correlation between land prices and financing costs during the pandemic thus gave local governments even greater incentives to manage and stabilize land prices.

B. Developers' Sales

While managing real estate prices may have helped support financing for local governments and firms during the pandemic, it also impeded the market's ability to adjust prices to sustain housing demand. This imposed direct costs on developers, who rely on housing sales to repay debt. As sales declined, developers' financial conditions worsened—reflected in a wave of high-profile defaults by developers such as Evergrande, Country Garden, and Sino-Ocean.

To assess the impact of price management on developers' housing sales, we conduct a developer-city-level panel regression. Since direct measurement of price management are unavailable, we use a city's pre-pandemic land dependence—measured by $LGFV\ Debt_2019_j$—

[22] 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.

as a proxy, following the analysis in Section IV. We specify the regression as follows:

$$Ln(House\ Sales)_{i,j,t} = \alpha_0 + \sum_{s=2015,t\neq 2019}^{2022} \alpha_s LGFV\ Debt_2019_j * Year_{s,t} + \beta CityControls_{j,t} + \gamma FirmControls_{i,t} + Fixed\ effects + \varepsilon_{i,j,t}. \quad (5)$$

The dependent variable, $Ln(House\ Sales)_{i,j,t}$, is the logarithm of new housing sales by developer *i* in city *j* and year *t*. We include city- and firm-level controls as in Equation (4), along with firm, city and year fixed effects to account for unobserved heterogeneity. The coefficients on the interaction terms between $LGFV\ Debt_2019_j$ and year dummies capture how developers' sales varied across cities with different levels of land dependence before the pandemic.

We use detailed annual data on new housing sales (revenue and area) by each developer from CREIS. The sample includes 172 domestic real estate firms publicly listed both in mainland China's A-share stock market and the Hong Kong stock market, covering the years 2015-2022.[23]

Estimation results are reported in Table 13. Columns (1) and (2) use sales value and area as dependent variable, respectively. The insignificant coefficients on the interaction terms for 2015-2018 suggest that the parallel trend assumption holds. Importantly, the coefficient for 2022, α_{2022}, is consistently and significantly negative across both measures of housing sales. For example, in Column (1), a one standard deviation increase in $LGFV\ Debt_2019$ is associated with a 10.33% additional decline in housing sales value in 2022.

This result cannot be explained by weaker fundamentals in more land-dependent cities, as Table 5 shows these cities experienced larger price increases in 2022. Rather, it supports our argument that local governments' price management may have prevented developers from lowering prices to sustain demand in response to the negative shock.

VII. Conclusion and Discussions

[23] To focus on cities where developers have a consistent presence, we include only those cities in which a developer recorded housing sales both before and after the outbreak of the Covid-19 pandemic.

This paper documents a pronounced divergence between price and volume in residential land and new housing transactions across Chinese cities during the Covid-19 pandemic. Rather than reflecting supply shortages alone, this disparity stems from local governments' deliberate price management, driven by their reliance on land sales and land-backed debt as key sources of fiscal financing.

Our research sheds light on China's ongoing real estate crisis. While much attention has focused on excessive construction—Glaeser et al. (2017) and Rogoff and Yang (2021, 2022)—and often blames profit-driven developers or speculative homebuyers, our findings highlight a more fundamental driver: the central role of local governments. As the primary suppliers of land, local governments rely heavily on land sales and land-backed debt to finance their budgets. This fiscal dependence, combined with pressure to stimulate local economic growth, has pushed developers toward overbuilding.

Previous studies, such as Fang et al. (2016) and Glaeser et al. (2017), emphasize that overly optimistic expectations among homebuyers have fueled China's real estate boom—often based on extrapolations of past growth. These expectations have likely been reinforced by strong government support for the housing market, further encouraging speculative behavior.

The deep involvement of local governments in the real estate sector reflects China's distinct hybrid economic model. It blends market forces—cultivated through four decades of reform—with enduring elements of state planning, evident in the frequent interventions by local governments and state-owned enterprises. This model allows the state to pursue broad policy goals, maintain social stability, and correct market failures, while also leveraging market mechanisms to improve efficiency. Market signals also guide state planning and provide performance metrics for local officials, as discussed by Li and Zhou (2005) and Song and Xiong (2024).

Yet, this hybrid system must navigate the inherent tensions between market dynamics and state intervention. Market forces can amplify distortions embedded in the state structure. Our study highlights this feedback loop in the real estate sector: as financial institutions extend credit to local governments based on land and property values, those same governments are incentivized to prop up prices, distorting market outcomes.

These distortions underscore the structural challenges China faces in resolving its real estate crisis. While bailing out distressed developers may provide short-term relief, it fails to address the root problem. A durable solution requires fundamental reform of the local government fiscal

system—specifically, reducing reliance on land sales and land-collateralized debt as core financing tools.

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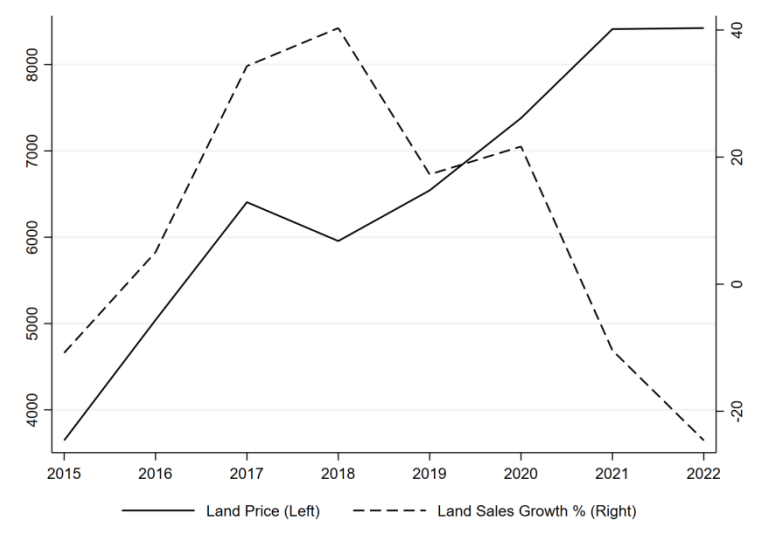
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Figure 1. Price and Volume Divergence in Real Estate Markets

This figure summarizes data from 173 cities listed in Table IA1 of the Internet Appendix from 2015 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).

ALT TEXT: Graphical presentation of divergent trends between transaction volume and prices in the Chinese real estate market during the COVID-19 period. Panel A shows data for residential land, while Panel B shows data for new residential housing.

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. Panel E shows the characteristics of each bond. Panel F demonstrates the characteristics of the real estate developers and their annual housing sales at the city level. The sample covers 133,971 land parcels in 173 cities, 31316 bonds issued by 2797 firms, and the balance sheet information of all the 172 publicly listed real estate developers from 2015 to 2022. *Ln*(*House Price*), *Ln*(*House Transaction Value*), *Ln*(*Land Price*), and *Ln*(*City Land Value*) are all inflation-adjusted to the 2015 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*)	1052	9.088	0.479	8.525	8.748	8.985	9.308	10.020
Ln(*House Transaction Units*)	1053	10.129	1.026	8.472	9.464	10.079	10.828	11.813
Ln(*House Transaction Area*)	1053	14.863	1.019	13.210	14.215	14.822	15.587	16.503
Ln(*House Transaction Value*)	1072	14.743	1.255	12.806	13.931	14.593	15.659	16.916
Ln(Vacant Housing Area)	775	13.777	0.991	12.262	13.088	13.758	14.396	15.446
Ln(*Constructing House Area*)	924	17.079	0.711	16.007	16.559	17.040	17.591	18.245
Ln(*Permit Area*)	706	14.861	1.216	12.824	14.150	14.852	15.763	16.640
Ln(*Permit Units*)	705	10.077	1.344	7.968	9.393	10.118	11.024	11.889
Panel B: Residential Land Transactions at the Transaction Level								
Ln(*Land Price*)	133965	7.897	1.064	6.217	7.202	7.873	8.591	9.661
Ln(*Land Area*)	133971	1.228	0.743	0.013	0.607	1.325	1.806	2.350
LGFV Dummy	133971	0.168	0.374	0	0	0	0	1
FAR	129690	2.496	1.159	1.111	1.800	2.200	2.917	4.900
Urban	133971	0.401	0.490	0	0	0	1	1
New Land	133971	0.505	0.500	0	0	1	1	1
Land Grade	125234	5.744	4.453	1	2	4	10	14
Tender	133971	0.004	0.061	0	0	0	0	0
Auction	133971	0.287	0.452	0	0	0	1	1
Panel C: Residential Land Transactions at the City Level								
Ln(*City Land Area*)	1384	5.406	1.016	3.694	4.860	5.549	6.114	6.751
Ln(*City Land Value*)	1384	13.625	1.728	11.314	12.861	13.718	14.540	15.973
Ln(*City Land Supply Area*)	1375	5.125	1.121	2.971	4.551	5.306	5.924	6.556
Ln(*City Land Supply Piece*)	1375	4.049	1.041	2.079	3.466	4.159	4.796	5.521
Land Price Growth Rate	1374	0.163	0.426	-0.348	-0.101	0.076	0.322	0.921
Land Area Growth Rate	1375	0.099	0.582	-0.578	-0.285	-0.003	0.309	1.205
Ln(*Land Price_AvgQ*)	4049	8.375	0.849	7.059	7.832	8.292	8.894	9.953
Failure Ratio (*Area*)	1374	0.107	0.131	0	0	0.056	0.171	0.388
Failure Ratio (*Piece*)	1374	0.108	0.126	0	0	0.060	0.177	0.377
LGFV Land Ratio (*Area*)	1383	0.168	0.169	0	0.026	0.118	0.263	0.523
LGFV Land Ratio (*Value*)	1383	0.159	0.174	0	0.018	0.094	0.243	0.551

Variable	N	Mean	SD	p5	p25	p50	p75	p95
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*)	1355	11.073	0.475	10.306	10.725	11.069	11.406	11.881
GDP Growth	1383	0.064	0.028	0.013	0.044	0.071	0.083	0.097
Fiscal Deficit	1381	0.094	0.068	0.014	0.045	0.083	0.124	0.209
Tax Ratio	1359	0.722	0.086	0.580	0.663	0.722	0.785	0.857
Secondary Sector	1377	0.422	0.084	0.268	0.374	0.423	0.481	0.554
Third Sector	1377	0.485	0.085	0.363	0.429	0.475	0.526	0.655
LGFV Leverage	1328	52.798	9.737	35.275	47.222	53.643	59.077	66.881
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
Panel F: Real Estate Developer Indicators								
Ln(*House Sales Value*)	16898	10.935	2.009	6.669	10.006	11.298	12.321	13.588
Ln(*House Sales Area*)	16898	10.642	1.895	6.452	9.851	11.042	11.939	13.055
Ln(*Asset*)	1286	10.691	1.598	8.065	9.644	10.705	11.877	13.331
Ln(*Sales*)	1289	9.022	1.789	6.091	7.933	9.033	10.175	12.206
Leverage	1286	0.710	0.171	0.333	0.639	0.750	0.824	0.907
ROA	1286	0.019	0.033	-0.039	0.011	0.020	0.033	0.062

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, *Year2015* 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*)
Year2015	-0.501***	-0.559***	-0.535***
	(-20.41)	(-10.74)	(-13.94)
Year2016	-0.439***	-0.470***	-0.476***
	(-18.94)	(-11.80)	(-14.00)
Year2017	-0.201***	-0.224***	-0.229***
	(-7.47)	(-6.49)	(-7.98)
Year2018	-0.078***	-0.089***	-0.082***
	(-4.03)	(-4.51)	(-4.73)
Year2020	0.070***	0.089***	0.054**
	(4.22)	(3.15)	(2.29)
Year2021	0.106***	0.152***	0.127***
	(5.22)	(5.88)	(5.64)
Year2022	0.117***	0.173***	0.110***
	(5.58)	(4.59)	(3.46)
Ln(*GDP per Capita*)		-0.140	-0.012
		(-1.52)	(-0.16)
GDP Growth		0.233	-0.326
		(0.51)	(-0.86)
Fiscal Deficit		0.867	-0.071
		(1.47)	(-0.14)
Tax Ratio		0.317	0.131
		(1.56)	(0.84)
Secondary Sector		0.293	0.471
		(0.30)	(0.51)
Third Sector		-0.168	0.288
		(-0.17)	(0.32)
Ln(*Land Area*)			0.083***
			(6.41)
FAR			0.241***
			(24.47)
Urban			0.519***
			(19.62)
New Land			-0.122***
			(-9.59)
Land Grade			-0.021***
			(-8.33)
Tender			0.036
			(0.36)
Auction			0.260***
			(9.39)
Constant	8.000***	9.193***	6.966***
	(392.29)	(6.97)	(6.33)
Observations	133,965	129,926	117,442
Adj. R-squared	0.384	0.385	0.536
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, *Year2015* 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 Value*)	
Year2015	-0.440***	-0.379***	-1.064***	-1.033***
	(-8.39)	(-4.11)	(-15.74)	(-8.06)
Year2016	-0.530***	-0.459***	-0.981***	-0.909***
	(-12.63)	(-6.52)	(-16.84)	(-9.32)
Year2017	-0.304***	-0.285***	-0.449***	-0.432***
	(-7.04)	(-5.19)	(-7.26)	(-5.96)
Year2018	-0.092***	-0.114***	-0.144***	-0.178***
	(-3.22)	(-3.15)	(-3.71)	(-3.09)
Year2020	0.136***	0.168***	0.207***	0.259***
	(4.75)	(3.86)	(5.78)	(4.62)
Year2021	-0.048	-0.037	0.045	0.096*
	(-1.24)	(-0.80)	(0.89)	(1.67)
Year2022	-0.420***	-0.431***	-0.456***	-0.407***
	(-8.67)	(-6.38)	(-7.46)	(-4.88)
Ln(GDP per Capita)		0.101		-0.131
		(0.41)		(-0.39)
GDP Growth		-0.008		0.040
		(-0.01)		(0.04)
Fiscal Deficit Rate		-0.136		-0.257
		(-0.08)		(-0.09)
Tax Ratio		0.720*		1.326**
		(1.82)		(2.56)
Secondary Sector		3.428		4.105
		(1.61)		(1.58)
Third Sector		3.310		4.291
		(1.54)		(1.60)
Constant	5.619***	0.937	13.980***	10.689**
	(231.58)	(0.32)	(449.66)	(2.38)
Observations	1,384	1,333	1,384	1,333
Adj. R-squared	0.829	0.833	0.892	0.887
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, *Year2015* 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.

	(1)	(2)	(3)	(4)
VARIABLES	*Failure Ratio* (*Piece*)		*Failure Ratio* (*Area*)	
Year2015	-0.090***	-0.052**	-0.086***	-0.064***
	(-10.98)	(-2.51)	(-10.51)	(-3.09)
Year2016	-0.089***	-0.065***	-0.083***	-0.070***
	(-11.77)	(-3.83)	(-10.50)	(-3.97)
Year2017	-0.068***	-0.048***	-0.066***	-0.054***
	(-8.44)	(-3.78)	(-8.93)	(-4.30)
Year2018	-0.025***	-0.016	-0.008	-0.001
	(-3.26)	(-1.61)	(-0.92)	(-0.06)
Year2020	0.060***	0.048***	0.053***	0.041***
	(6.22)	(3.64)	(5.51)	(3.09)
Year2021	0.112***	0.090***	0.120***	0.097***
	(9.38)	(6.29)	(9.46)	(6.53)
Year2022	0.085***	0.057***	0.085***	0.059***
	(7.12)	(3.35)	(6.91)	(3.52)
Ln(GDP per Capita)		0.085*		0.051
		(1.84)		(1.10)
GDP Growth		-0.054		-0.093
		(-0.30)		(-0.47)
Fiscal Deficit		-0.322		-0.550**
		(-1.29)		(-2.04)
Tax Ratio		-0.025		-0.024
		(-0.31)		(-0.28)
Secondary Sector		-0.948**		-1.097**
		(-2.13)		(-2.44)
Third Sector		-0.555		-0.747*
		(-1.23)		(-1.66)
Constant	0.110***	-0.113	0.105***	0.441
	(18.89)	(-0.21)	(18.53)	(0.88)
Observations	1,374	1,324	1,374	1,324
Adj. R-squared	0.451	0.453	0.412	0.415
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. *Year2015* 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 quarter 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)	(5)
VARIABLES			*Ln*(*Land Price*)		
*Land Dependence 2019*Year2015*	0.331	0.112			0.090
	(1.52)	(0.58)			(0.47)
*Land Dependence 2019*Year2016*	0.267	0.086			0.091
	(1.26)	(0.40)			(0.48)
*Land Dependence 2019*Year2017*	0.184	0.165			0.131
	(0.93)	(0.91)			(0.74)
*Land Dependence 2019*Year2018*	0.113	0.058			0.046
	(0.70)	(0.40)			(0.32)
*Land Dependence 2019*Year2020*	0.234	0.087			0.042
	(1.51)	(0.62)			(0.29)
*Land Dependence 2019*Year2021*	0.289*	0.175			0.080
	(1.79)	(1.20)			(0.55)
*Land Dependence 2019*Year2022*	0.433**	0.369**			0.271*
	(2.51)	(2.32)			(1.66)
*LGFV Debt 2019*Year2015*			0.025	0.010	0.006
			(1.21)	(0.53)	(0.27)
*LGFV Debt 2019*Year2016*			-0.001	0.004	-0.002
			(-0.03)	(0.16)	(-0.09)
*LGFV Debt 2019*Year2017*			0.010	0.017	0.014
			(0.49)	(1.06)	(0.76)
*LGFV Debt 2019*Year2018*			0.000	0.000	0.001
			(0.00)	(0.00)	(0.10)
*LGFV Debt 2019*Year2020*			0.015	0.015	0.017
			(1.15)	(1.31)	(1.30)
*LGFV Debt 2019*Year2021*			0.030	0.036***	0.034**
			(1.53)	(2.58)	(2.12)
*LGFV Debt 2019*Year2022*			0.037**	0.043***	0.037**
			(2.13)	(2.80)	(2.06)
Constant	9.453***	7.363***	9.141***	7.026***	7.489***
	(5.86)	(5.64)	(7.14)	(6.27)	(5.60)
Observations	121,216	109,354	129,926	117,442	109,354
Adj. R-squared	0.384	0.539	0.388	0.539	0.539
City Controls	YES	YES	YES	YES	YES
Transaction Controls	NO	YES	NO	YES	YES
Year/Quarter FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES

Table 6. The Divergence of Land Prices and Transaction Volumes Across Cities

The table reports the cross-sectional correlations between land price growth and transaction volume growth around the outbreak of the Covid-19 pandemic. The dependent variable, *Land Price Growth Rate,* is defined as the annual growth rate of transaction-area-weighted average land price in a given year and city. The main explanatory variables are the *Land Area Growth Rate* (the annual growth rate of the aggregated land transaction area for each city) and its interaction with a pandemic dummy, *Covid19*, which equals 1 for 2020-2022 and 0 otherwise. Columns (2)-(4) split the sample into three groups based on *Land Dependence_2019,* while Columns (5)-(7) split the sample into three groups based on *LGFV Debt_2019*. City Controls include *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. Variable definitions are provided in the Appendix. Robust standard errors are clustered at the city level, with t-statistics reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Land Price Growth Rate						
	All	*Land Dependence_2019*			*LGFV Debt_2019*		
		Low	Middle	High	Low	Middle	High
Land Area Growth Rate	0.034	-0.007	-0.029	0.143	0.018	0.103	-0.013
	(0.81)	(-0.13)	(-0.44)	(1.41)	(0.24)	(1.39)	(-0.21)
*Land Area Growth Rate * Covid19*	-0.145**	-0.126	-0.055	-0.166	-0.092	-0.201*	-0.160**
	(-2.50)	(-1.45)	(-0.63)	(-1.36)	(-0.83)	(-1.98)	(-2.05)
Constant	0.678	3.300*	3.629	-3.825	2.450	1.566	-1.924
	(0.61)	(1.86)	(1.19)	(-1.58)	(1.18)	(1.01)	(-0.76)
Observations	1,325	394	392	389	445	447	433
Adj. R-squared	0.068	0.059	0.058	0.030	0.057	0.043	0.106
City Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 7. 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*) of Panel A and Panel B 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, *Year2015* to *Year2022*, are year dummies. The Columns (2)-(4) divide the cities into three subsamples according to their *Land Dependence_2019.* Similarly, the Columns (5)-(7) divide the cities into three subsamples according to their *LGFV Debt_2019*. 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.

Panel A: LGFV Land Ratio (Area)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LGFV Land Ratio (*Area*)						
	All	*Land Dependence_2019*			*LGFV Debt_2019*		
		Low	Middle	High	Low	Middle	High
Year2015	0.002	0.020	-0.013	-0.116*	-0.025	0.062**	-0.066
	(0.10)	(0.78)	(-0.48)	(-2.00)	(-0.91)	(2.04)	(-1.45)
Year2016	0.003	0.031	-0.011	-0.091**	-0.019	0.019	-0.021
	(0.17)	(1.20)	(-0.44)	(-2.09)	(-0.78)	(0.72)	(-0.56)
Year2017	-0.004	0.039*	-0.027	-0.072**	-0.007	0.039	-0.056**
	(-0.27)	(1.97)	(-1.41)	(-2.25)	(-0.35)	(1.62)	(-2.06)
Year2018	-0.002	-0.010	-0.002	-0.014	0.003	-0.001	-0.009
	(-0.16)	(-0.73)	(-0.17)	(-0.58)	(0.23)	(-0.06)	(-0.40)
Year2020	0.033**	0.028	0.039	0.046*	0.037*	0.003	0.054*
	(2.36)	(1.19)	(1.44)	(1.89)	(1.80)	(0.16)	(1.98)
Year2021	0.060***	0.065***	0.023	0.127***	0.051***	0.049**	0.088***
	(4.99)	(3.19)	(1.06)	(4.82)	(3.02)	(2.29)	(3.59)
Year2022	0.195***	0.180***	0.182***	0.269***	0.175***	0.156***	0.258***
	(10.66)	(6.43)	(5.54)	(6.43)	(5.43)	(4.62)	(9.25)
Constant	-0.565	-2.075**	-0.984	3.823**	-0.188	-1.548	0.896
	(-0.80)	(-2.23)	(-0.64)	(2.56)	(-0.22)	(-1.22)	(0.60)
Observations	1,332	401	392	389	446	453	433
Adj. R-squared	0.572	0.438	0.627	0.607	0.438	0.539	0.550
City Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES

Panel B: LGFV Land Ratio (Valuation)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LGFV Land Ratio (Value)						
	All	*Land Dependence_2019*			*LGFV Debt_2019*		
		Low	Middle	High	Low	Middle	High
Year2015	0.034*	0.063***	-0.016	-0.063	0.019	0.088***	-0.040
	(1.69)	(2.71)	(-0.55)	(-1.16)	(0.75)	(2.86)	(-0.89)
Year2016	0.018	0.052*	-0.013	-0.052	0.005	0.024	-0.005
	(1.05)	(1.97)	(-0.48)	(-1.23)	(0.21)	(0.89)	(-0.12)
Year2017	-0.004	0.051**	-0.041**	-0.063**	0.003	0.028	-0.058**
	(-0.34)	(2.49)	(-2.13)	(-2.01)	(0.16)	(1.16)	(-2.06)
Year2018	-0.003	0.002	-0.010	-0.021	0.002	-0.004	-0.008
	(-0.28)	(0.12)	(-0.70)	(-0.93)	(0.18)	(-0.22)	(-0.38)
Year2020	0.032**	0.024	0.043	0.046	0.037*	0.003	0.047
	(2.23)	(1.02)	(1.58)	(1.57)	(1.69)	(0.16)	(1.67)
Year2021	0.055***	0.057**	0.037	0.110***	0.041**	0.056**	0.077***
	(4.38)	(2.66)	(1.61)	(4.03)	(2.45)	(2.40)	(2.96)
Year2022	0.211***	0.190***	0.215***	0.288***	0.194***	0.167***	0.277***
	(10.56)	(6.01)	(5.67)	(6.46)	(5.51)	(4.48)	(9.15)
Constant	-0.643	-2.080**	-1.209	3.315**	-0.700	-1.294	0.786
	(-0.95)	(-2.26)	(-0.78)	(2.45)	(-0.97)	(-1.05)	(0.52)
Observations	1,332	401	392	389	446	453	433
Adj. R-squared	0.550	0.415	0.569	0.609	0.414	0.571	0.511
City Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES

Table 8. 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, *Year2015* 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	-0.082**	-0.082**	-0.090**
	(-2.06)	(-2.05)	(-2.52)
*LGFV Dummy * Year2015*	0.239***	0.240***	0.173***
	(4.64)	(4.63)	(3.84)
*LGFV Dummy * Year2016*	0.030	0.028	-0.016
	(0.43)	(0.40)	(-0.21)
*LGFV Dummy * Year2017*	-0.089	-0.085	-0.077
	(-1.59)	(-1.52)	(-1.35)
*LGFV Dummy * Year2018*	-0.003	-0.004	-0.043
	(-0.05)	(-0.08)	(-0.87)
*LGFV Dummy * Year2020*	0.075*	0.081**	0.070*
	(1.94)	(2.08)	(1.95)
*LGFV Dummy * Year2021*	0.055	0.057	0.064
	(1.14)	(1.16)	(1.59)
*LGFV Dummy * Year2022*	0.157***	0.154***	0.117***
	(3.34)	(3.27)	(2.82)
Ln(Land Area)			0.082***
			(6.47)
FAR			0.241***
			(24.59)
Urban			0.522***
			(19.83)
Land Grade			-0.121***
			(-9.51)
New Land			-0.021***
			(-8.39)
Tender			0.039
			(0.39)
Auction			0.257***
			(9.37)
Constant	7.899***	9.005***	6.818***
	(464.76)	(6.94)	(6.31)
Observations	133,965	129,926	117,442
Adj. R-squared	0.387	0.389	0.539
City Controls	NO	YES	YES
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table 9. 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, *Year2015* 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. 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	*LGFV Leverage* (%)
Year2015	-2.951**
	(-2.03)
Year2016	0.106
	(0.10)
Year2017	1.481**
	(2.05)
Year2018	-0.111
	(-0.27)
Year2020	0.858*
	(1.74)
Year2021	3.693***
	(4.83)
Year2022	4.061***
	(4.05)
Constant	-10.846
	(-0.28)
Observations	1,279
Adj. R-squared	0.750
City Controls	YES
City FE	YES

Table 10. 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, *Year2015* 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)*
Year2015	-0.343***	0.246	0.223	0.089
	(-9.76)	(1.54)	(1.37)	(0.51)
Year2016	-0.347***	0.131	0.094	-0.169
	(-14.21)	(1.37)	(0.98)	(-1.63)
Year2017	-0.210***	-0.123	-0.143*	-0.288***
	(-10.38)	(-1.42)	(-1.66)	(-3.25)
Year2018	-0.072***	-0.075	-0.084*	-0.123**
	(-6.11)	(-1.48)	(-1.66)	(-2.36)
Year2020	0.030**	0.073	0.071	0.075
	(2.42)	(1.26)	(1.23)	(1.21)
Year2021	0.059***	-0.119*	-0.115*	-0.051
	(4.02)	(-1.78)	(-1.73)	(-0.74)
Year2022	0.054**	-0.414***	-0.394***	-0.379***
	(2.34)	(-4.09)	(-3.91)	(-3.62)
Constant	9.103***	4.973	9.922**	6.488
	(10.91)	(1.23)	(2.44)	(1.53)
Observations	1,013	1,014	1,014	1,033
Adj. R-squared	0.943	0.761	0.757	0.823
City Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES

Table 11. DID Analysis of New House Price and Sales Permits

This table examines the impact of local governments' fiscal conditions on new house prices and the issuance of sales permits. The dependent variable *Ln*(*House Price*) is the logarithm of the inflation-adjusted housing price in a given city and year. The dependent variables *Ln*(*Permit Area*) and *Ln*(*Permit Units*) denote the logarithm of the total area and number of new housing units approved for sale in a given city and year, respectively. The independent variable, *LGFV Debt_2019,* is defined as the ratio of a city's aggregated LGFV liabilities its total fiscal revenue in 2019. *Year2015* to *Year2022* are year dummies. We also control for the lagged logarithm of housing transactions, *Ln*(*House Transaction Area t-1*) and *Ln*(*House Transaction Units t-1*), as well as city-level characteristics: *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. All regressions include both city and year fixed effects. Robust standard errors are clustered at the city level, with t-statistics reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
VARIABLES	*Ln(House Price)*	*Ln*(*Permit Area*)	*Ln*(*Permit Units*)
*LGFV Debt_2019*Year2015*	-0.001	-0.015	0.001
	(-0.08)	(-0.14)	(0.01)
*LGFV Debt_2019*Year2016*	0.002	-0.153*	-0.114
	(0.17)	(-1.72)	(-1.12)
*LGFV Debt_2019*Year2017*	-0.011	-0.092	-0.104
	(-1.17)	(-0.93)	(-0.92)
*LGFV Debt_2019*Year2018*	-0.011	-0.048	-0.055
	(-1.51)	(-0.71)	(-0.80)
*LGFV Debt_2019*Year2020*	0.006	-0.023	-0.020
	(1.21)	(-0.42)	(-0.37)
*LGFV Debt_2019*Year2021*	0.018**	0.017	0.012
	(2.08)	(0.31)	(0.21)
*LGFV Debt_2019*Year2022*	0.022**	-0.132**	-0.143**
	(2.01)	(-2.06)	(-1.99)
Ln(House Price)		0.847**	0.809**
		(2.52)	(2.25)
Ln(House Transaction Area t-1)		0.118	
		(1.19)	
Ln(House Transaction Units t-1)			0.084
			(0.66)
Constant	9.390***	-5.952	-16.970
	(11.25)	(-0.41)	(-1.04)
Observations	1,005	564	563
Adj. R-squared	0.942	0.704	0.693
City Controls	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES

Table 12. Land Price, Firm Financing Cost and City Investment

The table reports the relationship between land price and the financing cost of local firms. The dependent variables are *Coupon Spread,* the coupon rate minus the Chinese Treasury yield indices of similar maturity. The key independent variable is *Ln*(*Land Price_AvgQ*), which is the logarithm of the average land price in the quarter prior to the bond issuance. *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 Column (1) and (2) cover the full sample of bonds. The Column (3) uses the subsample of bonds issued by non-LGFV firms, while the Column (4) uses the subsample of bonds issued by LGFV. The quarter, firm, and bond type fixed effects are 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.

VARIABLES	(1) *Coupon Spread*	(2) *Coupon Spread*	(3) *Coupon Spread*	(4) *Coupon Spread*
	All Firms	*All Firms*	*Non-LGFV*	*LGFV*
Ln(*Land Price AvgQ*)	-0.053*	-0.016	0.024	-0.071
	(-1.70)	(-0.45)	(0.86)	(-0.82)
Ln(*Land Price AvgQ*) * *Covid19*		-0.063**	-0.108***	0.025
		(-2.25)	(-3.34)	(0.34)
Ln(*Issue Amount*)	-0.041**	-0.040**	-0.043**	-0.028
	(-2.45)	(-2.38)	(-2.46)	(-1.63)
Maturity	-0.030**	-0.030**	-0.014	-0.039***
	(-2.44)	(-2.43)	(-0.85)	(-2.74)
TripleA	-0.481***	-0.494***	-0.288	-0.579***
	(-4.45)	(-4.52)	(-1.49)	(-5.24)
DoubleAplus	-0.181**	-0.193**	0.046	-0.316***
	(-2.00)	(-2.10)	(0.24)	(-5.03)
SOE	-0.479***	-0.479***	-0.480***	
	(-5.08)	(-4.75)	(-3.66)	
Ln(Asset)	-0.086	-0.071	0.087	-0.317
	(-0.58)	(-0.47)	(0.71)	(-1.42)
Ln(Sales)	-0.037	-0.043	-0.105**	0.009
	(-1.00)	(-1.20)	(-2.11)	(0.20)
Leverage	0.616	0.573	0.658	0.420
	(1.35)	(1.26)	(1.39)	(1.05)
ROA	-2.086*	-2.222*	-2.038*	1.831
	(-1.69)	(-1.79)	(-1.78)	(0.60)
Constant	19.134***	18.573***	5.025	38.464***
	(2.69)	(2.64)	(0.80)	(3.21)
Observations	29,246	29,246	19,002	10,225
Adj. R-squared	0.808	0.808	0.821	0.782
City Controls	YES	YES	YES	YES
Year/Quarter FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Bond Type FE	YES	YES	YES	YES

Table 13. DID Analysis of Developers' Housing Sales

The table reports the impact of local government's real estate management on developers' house sales. The dependent variables *Ln*(*House Sales Value*) and *Ln*(*House Sales Area*) denote the logarithm of annual housing sales in value and area for each developer across cities. The independent variable *LGFV Debt_2019* equals the aggregated LGFV liability of a city divided by the city's total fiscal revenue in 2019. (total fiscal revenue = general public budget revenue + transfer income + governmental fund revenue + state-owned capital operation income). *Year2015* to *Year2022* are year dummies. The Developer Controls include *Ln*(*Asset*), *Leverage, Ln*(*Sales*), and *ROA*, while the City Controls contain *Ln*(*GDP per Capita*), *GDP Growth*, *Fiscal Deficit*, *Tax Ratio*, *Secondary Sector* and *Third Sector*. The year, developer, and city fixed effects are included in all columns. The *t-statistics* of robust standard errors clustered at the developer level is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	*Ln*(*House Sales Value*)	*Ln*(*House Sales Area*)
*LGFV Debt_2019*Year2015*	-0.034	-0.034
	(-0.91)	(-0.96)
*LGFV Debt_2019*Year2016*	0.008	0.022
	(0.22)	(0.63)
*LGFV Debt_2019*Year2017*	-0.017	-0.006
	(-0.45)	(-0.16)
*LGFV Debt_2019*Year2018*	0.029	0.041
	(1.01)	(1.47)
*LGFV Debt_2019*Year2020*	-0.008	-0.006
	(-0.35)	(-0.25)
*LGFV Debt_2019*Year2021*	-0.008	-0.009
	(-0.27)	(-0.33)
*LGFV Debt_2019*Year2022*	-0.074**	-0.073**
	(-2.17)	(-2.11)
Constant	11.366***	10.731***
	(2.95)	(2.80)
Observations	16,171	16,171
Adj. R-squared	0.306	0.262
Developer Controls	YES	YES
City Controls	YES	YES
Year FE	YES	YES
Developer FE	YES	YES
City FE	YES	YES

Appendix

Table A1. 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(Vacant Housing Area)	The Logarithm of the area of vacant house.	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 transacted in area.	Hectare
Ln(City Land Value)	The natural logarithm of the total land transacted in value.	Ten thousand yuan

Variable	Definition	Unit
Ln(City Land Supply Area)	The natural logarithm of the total area of supplied land in the primary market.	Hectare
Ln(City Land Supply Piece)	The natural logarithm of the total number of land transactions in the primary market.	
Land Price Growth Rate	The annual growth rate of transaction-area-weighted average land price in a given year and city.	
Land Area Growth Rate	The annual growth rate of the aggregated land transaction area for each city.	
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.	
Bond market indicators		
Coupon Spread	Coupon rates minus the Chinese Treasury yield indices with similar maturity.	%
Ln(Issue Amount)	The natural logarithm of bond issue amount.	Million

Variable	Definition	Unit
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.	
Real estate developer indicators		
Ln(House Sales Value)	The natural logarithm of the residential house sales of the developer in the specific city and year (in value).	Ten thousand yuan
Ln(House Sales Area)	The natural logarithm of the residential house sales of the developer in the specific city and year (in area).	Square meter
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.	

Internet Appendix

Table IA1. 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 IA2. 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 IA3. Dynamics of Land Transaction Size and Count

This table reports the dynamics of land transaction size and transaction count in cities around the outbreak of the COVID-19 pandemic. The dependent variables are *Ln*(*Transaction Size*), the logarithm of the land transaction size for each land parcel, and *Ln*(*Transaction Count*), the logarithm of the total number of land transactions for each city and year. The main independent variables are year dummies from 2015 to 2022. All regressions include city fixed effects. The *t-statistic*, based on 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*(*Transaction Size*)	(1) *Ln*(*Transaction Count*)
Year2015	-0.108***	-0.117
	(-4.12)	(-1.42)
Year2016	-0.096***	-0.252***
	(-4.40)	(-3.75)
Year2017	-0.053***	-0.179***
	(-3.17)	(-3.21)
Year2018	-0.016	-0.042
	(-1.42)	(-1.36)
Year2020	0.033**	0.115***
	(2.00)	(3.02)
Year2021	-0.011	-0.044
	(-0.62)	(-1.01)
Year2022	-0.053***	-0.362***
	(-2.60)	(-6.45)
Constant	-0.048	0.023
	(-0.07)	(0.01)
Observations	117,447	1,333
Adj. R-squared	0.287	0.855
City Controls	YES	YES
Transaction Controls	YES	NO
City FE	YES	YES

Table IA4. Dynamics of Land Supply

The table reports the dynamics of the land supply in cities around the outbreak of the Covid-19 pandemic. The dependent variables are *Ln*(*City Land Supply Piece*) and *Ln*(*City Land Supply Area*), the logarithm of the total pieces or area of supplied land in the primary market. The main independent variables, *Year2015* to *Year2022*, are year dummies. The main independent variables, *Year2015* 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.

	(1)	(2)	(3)	(4)
VARIABLES	*Ln*(*City Land Supply Piece*)		*Ln*(*City Land Supply Area*)	
Year2015	-0.056	-0.049	-0.388***	-0.343**
	(-1.07)	(-0.44)	(-6.20)	(-2.43)
Year2016	-0.392***	-0.385***	-0.701***	-0.682***
	(-7.32)	(-4.31)	(-10.25)	(-5.89)
Year2017	-0.230***	-0.231***	-0.363***	-0.363***
	(-5.61)	(-3.54)	(-6.91)	(-4.48)
Year2018	-0.019	-0.032	-0.044	-0.058
	(-0.50)	(-0.76)	(-0.94)	(-1.07)
Year2020	0.049	0.101	-0.009	0.023
	(1.31)	(1.51)	(-0.20)	(0.27)
Year2021	-0.178***	-0.147**	-0.229***	-0.183**
	(-3.26)	(-2.09)	(-3.67)	(-2.26)
Year2022	-0.368***	-0.329***	-0.513***	-0.475***
	(-6.68)	(-4.08)	(-7.56)	(-5.00)
Constant	4.198***	3.797	5.406***	4.912
	(156.64)	(1.24)	(156.23)	(1.30)
Observations	1,375	1,325	1,375	1,325
Adj. R-squared	0.769	0.767	0.718	0.721
City Controls	NO	YES	NO	YES
City FE	YES	YES	YES	YES

Table IA5. 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

	2015-2019		2020-2022			
	(1)	(2)	(3)	(4)	(4)- (2)	t-statistics
	N	Mean	N	Mean		
FAR	64027	2.637	36870	2.438	-0.199	-25.304***
Land Grade	64027	5.719	36870	5.758	0.040	1.340
Urban	64027	0.384	36870	0.409	0.025	7.955***

Panel B: Land Acquired by LGFVs

	2015-2019		2020-2022			
	(1)	(2)	(3)	(4)	(4)- (2)	t-statistics
	N	Mean	N	Mean		
FAR	10126	2.412	10192	2.210	-0.202	-16.467***
Land Grade	10126	5.692	10192	5.728	0.037	0.650
Urban	10126	0.476	10192	0.484	0.008	1.156

Table IA6. 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	0.031**	0.012	0.114
	(2.00)	(0.36)	(0.97)
LGFV Dummy * Covid19	0.011	-0.044	-0.044
	(0.74)	(-1.23)	(-0.30)
Ln(GDP per Capita)	-0.088**	-0.288***	-0.241
	(-2.02)	(-2.69)	(-0.42)
GDP Growth	0.127	0.772	2.231
	(0.79)	(1.64)	(0.86)
Fiscal Deficit	0.831***	0.848	-6.170*
	(3.07)	(1.25)	(-1.69)
Tax Ratio	-0.038	0.178	-0.211
	(-0.46)	(0.75)	(-0.17)
Secondary Sector	-0.164	-1.066	12.188**
	(-0.49)	(-0.89)	(2.34)
Third Sector	-0.544	-1.062	18.153***
	(-1.51)	(-0.85)	(3.30)
Ln(Land Area)	0.160***	-0.348***	-0.156*
	(19.26)	(-14.29)	(-1.80)
New Land	-0.056***	-0.185***	0.492***
	(-7.27)	(-8.89)	(6.14)
Tender	-0.076	0.199*	-0.023
	(-1.33)	(1.89)	(-0.02)
Auction	0.021	0.028	-0.269
	(0.95)	(0.74)	(-1.16)
Constant	1.477***	6.915***	-5.061
	(2.69)	(4.64)	(-0.77)
Observations	129,931	125,716	121,402
Adj. R-squared	0.275	0.238	0.236
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table IA7. 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). *Year2015* 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.

VARIABLES	(1) *Ln*(*Land Price*)	(3) *Ln*(*Land Price*)	(2) *Ln*(*Land Price*)
FAR * *Year2015*	0.003		
	(0.16)		
FAR * *Year2016*	-0.024		
	(-0.99)		
FAR * *Year2017*	0.004		
	(0.20)		
FAR * *Year2018*	-0.014		
	(-0.85)		
FAR * *Year2020*	-0.025		
	(-1.43)		
FAR * *Year2021*	-0.025		
	(-1.21)		
FAR * *Year2022*	-0.032		
	(-1.46)		
Land Grade * *Year2015*		-0.004	
		(-0.72)	
Land Grade * *Year2016*		-0.008	
		(-1.15)	
Land Grade * *Year2017*		-0.005	
		(-0.93)	
Land Grade * *Year2018*		-0.002	
		(-0.58)	
Land Grade * *Year2020*		-0.005	
		(-1.40)	
Land Grade * *Year2021*		-0.001	
		(-0.34)	
Land Grade * *Year2022*		-0.004	
		(-0.98)	
Urban * *Year2015*			-0.142***
			(-3.46)
Urban * *Year2016*			-0.042
			(-0.91)
Urban * *Year2017*			-0.034
			(-0.84)
Urban * *Year2018*			-0.013
			(-0.40)

VARIABLES	(1) *Ln*(*Land Price*)	(3) *Ln*(*Land Price*)	(2) *Ln*(*Land Price*)
Urban * *Year2020*			-0.052*
			(-1.72)
Urban * *Year2021*			-0.079**
			(-2.35)
Urban * *Year2022*			-0.085**
			(-2.37)
Ln(Land Area)	0.081***	0.081***	0.080***
	(6.28)	(6.26)	(6.25)
FAR	0.253***	0.242***	0.242***
	(13.70)	(24.71)	(24.57)
Urban	0.520***	0.521***	0.574***
	(19.72)	(19.70)	(17.05)
New Land	-0.121***	-0.121***	-0.121***
	(-9.51)	(-9.53)	(-9.52)
Land Grade	-0.021***	-0.018***	-0.021***
	(-8.41)	(-4.91)	(-8.34)
Tender	0.040	0.043	0.038
	(0.40)	(0.43)	(0.39)
Auction	0.259***	0.259***	0.258***
	(9.42)	(9.48)	(9.42)
Constant	6.752***	6.875***	6.766***
	(6.31)	(6.33)	(6.30)
Observations	117,442	117,442	117,442
Adj. R-squared	0.539	0.539	0.539
City Controls	YES	YES	YES
Year/Quarter FE	YES	YES	YES
City FE	YES	YES	YES

Table IA8. 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,

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				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

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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.