The Political Roots of China's Housing Vacancies

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Abstract

China has a vast number of unsold and unoccupied homes. Can incentives faced by local politicians explain this puzzle? In China, local governments are monopolists in selling land use-rights, which is a key input for the housing market. City managers, the leader of local governments, are promoted based on the performance of the local economy. They also use land revenues to fund local government expenditures. I develop and estimate a dynamic, infinite-horizon model of land supply. In this model, forward-looking city managers choose how much land to make available for the private sector, in order to both boost local economic growth and generate local government revenues. Due to political concerns such as achieving GDP growth rate targets, city managers tend to allocate more land to the private sector than the revenue-maximizing level. By estimating the structural model of equilibrium land supply with manager-city-year level data, I infer city managers' weights on career advancement relative to land revenues. Using the parameter estimates from the model, I then estimate the impact of political incentives on land allocation. Overall, city managers sell 7.4% more land between 2003 and 2012 relative to the counterfactual in which city managers have no GDP growth incentives. This land oversupply is 12.5% in smaller cities and 3.7% in larger cities. Finally, converting land to housing construction, the estimated impacts explain 23.2% to 27.7% of unsold homes.

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1 Introduction

China has an enormous amount of housing vacancies. The gap between total residential floor space started and total housing sold reached 2.85 billion square meters (30.7 billion square feet) in 2018. Without new construction, it would take up to two years to sell this inventory (Rogoff and Yang 2020). In contrast, new single-family houses for sale in the U.S. can only last 6.6 months of supply during the same period.[1] Given that the real estate sector accounts for more than 25% of China's GDP, crises such as the Evergrande fiasco due to over-borrowing and over-building could shock the financial system and drag on the whole economy.[2]

Why does China have such an unusually high rate of housing vacancies? In this paper, I investigate the role that politics play in explaining this puzzle. By law, the state owns all urban land. Local governments are monopolist sellers of land leaseholds and stipulate construction requirements, such as the floor-to-area ratio. Property developers also rely on state-owned banks to borrow and build. Thus, local governments hold vast sway over housing construction. City managers, the head of local governments, face a trade-off in making land supply decisions. Selling more land increases housing construction and local economic growth, which is the basis for their promotion (Li and Zhou (2005), Maskin, Qian, and Xu (2000)). However, selling too much land too quickly decreases land revenues needed for financing local government expenditures. Therefore, they have both the tools and incentives to influence local economic activities.

In order to quantify the impacts of political incentives in China's land and housing market, I need to address three issues. First, while city managers care about both local economic growth and land revenues, the relative weight on each component is not directly observed. Second, there was a major change in China's national leadership when President Xi took office in 2013, and different presidents emphasized different political incentives. Third, GDP growth rate targets are endogenous since current economic performance affects future growth targets.

My approach is to build a dynamic structural model that rationalizes city managers' land supply decisions. Modeling city managers' behaviors enables me to infer their relative weight on political incentives by president and simulate their optimal choices in response to hypothetical promotion schemes. Moreover, it flexibly incorporates political cycles and allows for heterogeneity in city managers' past performance. Finally, the model accounts for city managers' expectations of target transitions in a rational way: today's GDP growth

[1] Source: The U.S. Census https://www.census.gov/construction/nrs/pdf/newressales_201812.pdf

[2] Source: The New York Times https://www.nytimes.com/article/evergrande-debt-crisis.html?

affects future growth and target in the same way that yesterday's GDP growth affects today's target and actual growth.

This model highlights both static and intertemporal trade-offs that city managers encounter. First, in a given period, to finance local government expenditures, city managers would want to maximize land profits delivered in this period. However, their probability of promotion depends on their history of hitting GDP growth rate targets. Thus, the incentive to boost economic growth encourages city managers to inject land into the economy and dampens the land profits motivation. Second, across different periods, higher GDP growth today increases both city managers' chance of advancing tomorrow and future land profits. However, the future GDP growth target is positively correlated with today's economic conditions, so city managers do not want to stimulate the economy to the extent that it makes future targets unattainable. Therefore, it is unclear what role political incentives play in the equilibrium land supply.

The structural model has three components: an aggregate economic environment of the city, a dynamic political system for promotion, and a forward-looking city manager who is also a monopoly land supplier. The first component is characterized by the inter-dependence between a city's economy and its local land market. Specifically, cities' economic growth is a function of local production that takes land as input, and developers' willingness to pay in the land market, in turn, depends on the city's overall economic condition. Also, the cost of leasing land varies with the population density of the city. Second, the political system features an evaluation scheme based on city managers' history of economic performance. It also introduces a rule for setting future GDP growth targets, which depends on the current period's actual GDP growth rate relative to the target. The third component characterizes city managers' infinite-horizon optimization problem: they make land supply decisions to maximize the current period payoff and the expected utility in future periods.

To recover city managers' weights on political incentives, I construct manager-city-year level panel data for Chinese cities at the provincial or prefectural level from 2003 to 2017. For each city-year observation, the data contain information on the aggregate area of land being leased via public auctions and total land revenues, from which I compute the average land price. I also observe cities' annual GDP growth rate target and the actual GDP growth rate. Finally, I match the data with information on city managers, such as their year of appointment and demographics. From these data, I have a complete picture of the land market equilibrium and can connect city managers' incentives, behavior, and career outcomes over time.

Building on this data, I estimate the structural model using a two-step procedure. The first step estimates four equations that characterize cities' economic environment and political system. The first equation estimates the current period's GDP growth rate as a function of its lag values and land supply. To address the concern of unobserved city manager ability, I instrument for a city's GDP growth using neighboring cities' economic growth. It captures common regional shocks that are orthogonal to a city manager's ability. The second equation estimates the aggregate land demand. I measure local governments' need to finance expenditures with land revenues and use it as a supply shifter, assuming it is orthogonal to demand shocks in the local land market. In the third equation, I estimate city managers' promotion function. To incorporate political cycles and regime shifts, I allow the importance of economic performance to vary across time periods. Moreover, city managers are only evaluated on their own performance history and are not responsible for the consequences of their predecessors' acts. Lastly, I estimate the GDP growth rate target equation. I allow both the level and slope of tomorrow's target to depend on today's realization relative to today's target. In estimating all four equations, I take advantage of the panel data structure and add city fixed effects to account for unobserved variables fixed over time.

The second stage estimates city managers' weights on political incentives relative to expected land profits, as well as land cost parameters. I adopt methods from the literature on single-agent dynamics with discrete choice. Given that the distributions of the control and state variables are very sparse across cities but concentrated in a small range for a given city, I discretize the control variable and the state variables separately for each city. The estimation has two layers. In the inner loop, I compute the optimal land supply predicted by the model for a given set of dynamic parameters. The computational challenge is that, given the large state space, fully solving the model for all cities together suffers from the curse of dimensionality. Instead of treating city as a state variable, I iterate on each city's value function and solve the corresponding optimization problem separately. It greatly reduces the dimension of the state space and leaves a much smaller problem for each city. In the outer loop, I search over the values of dynamic parameters to minimize the sum of squared differences between observed land supply and the optimal supply predicted by the model. Identification comes from several sources: variation in the returns to economic performance, as induced by political cycles and regime shifts; variation in the distance from pre-determined GDP growth rate target, as driven by regional economic shocks; and variation in land profits brought about by local governments' different needs in financing expenditures.

The estimation reveals the following results. First, the relative weights that city managers put on political incentives vary by regime. From 2003 to 2012, the promotion scheme emphasized economic growth. Normalizing the weight on expected land profits to one, city managers' relative weight on hitting GDP growth rate targets exceeds 300. In contrast, Mr. Xi assumed the presidency in 2013 and announced that government officials should not be simply evaluated by GDP growth.[3] The estimated promotion function captures this change and no longer rewards achieving growth targets. As a result, the relative weight on hitting GDP growth targets drops sharply to -41. This negative relative weight implies that city managers redirect resources to other channels of promotion. Second, city managers' marginal cost of selling land leaseholds is higher if a city has a higher population density. Specifically, the cost increases by 320 Yuan per square meter for an extra person per hundred square meters. The estimated land profits are not trivial. For example, the median city in our sample earns 1.59 billion Yuan from selling land leaseholds, which accounts for nearly 25% of its government income.

With the estimated model parameters, I conduct several counterfactual analyses to evaluate the impact of political incentives on city managers' optimal land supply decisions. I benchmark these effects against the model predictions using the estimated parameters. In the baseline analysis, city managers care about both promotion probability and expected land profits. Before 2012, the chance of promotion increases with the cumulative probability of hitting the GDP growth target. After 2012, economic growth is not statistically important for career advancement.

The main counterfactual considers a world in which city managers put zero weight on getting promoted via the economic growth channel before 2012, holding their preferences after 2012 the same as in the baseline. Given this set of counterfactual parameter values, I solve city managers' optimization problem by re-computing their value functions and the corresponding optimal quantity of land supply.

I find that about 7.4% of the leased land is made available on the market due to economic growth incentives. The extra land quantity between the baseline and the counterfactual with no GDP growth incentives is around 0.41 million square meters for an average city annually. Aggregated across 213 cities in the sample, it amounts to 873.3 million square meters (337.2 square miles) during the ten years between 2003 to 2012. Moreover, I convert the impact of political incentives on land supply into impact on construction using a simple accounting method. The average floor space of extra construction ranges from 0.31 to 0.37 million square meters for a city-year, which aggregates to 660.3 to 788.1 million square meters across 213 cities in ten years. This extra construction explains 23.2% to 27.7% of the gap between the cumulative housing area started and housing sold, which is one way to measure excess housing supply.

To analyze the distributional impacts of political incentives on the land market, I divide cities into four tiers based on their population and GDP per capita. Tier one cities are the

[3] See Reuter's report https://www.reuters.com/article/us-china-economy-factbox/factbox-china-comment-xi-says-gdp-not-the-only-performance-metric-idUKBRE96007W20130701

largest, and tier four cities are the smallest. Tier four cities, on average, have an extra land supply of 0.49 million square meters annually, which is 12.52% of the total land area being leased. The effects are 6.79% in tier three cities and 1.27% in tier two cities. Compared with other cities, tier four cities have the smallest populations and the lowest average GDP per capita level. Without government support, these cities would underperform GDP growth targets more than their counterparts. Moreover, because of the low population density, the cost of selling land is lower in tier four cities, making housing construction a favorable tool to stimulate the economy. While political incentives generally cause land oversupply, these estimates imply that smaller cities with low-income populations experience larger market distortions.

Related Literature

This paper adds to the rich literature that studies housing booms and excess supply of housing. Much of this literature is focused on the demand for housing (e.g., Drechsler, Savov, and Schnabl (2021), Foote, Loewenstein, and Willen (2021), Kaplan, Mitman, and Violante (2020)). In particular, many papers document the imbalance between demand and supply in China's housing market (Rogoff and Yang (2020), Chen and Wen (2017), Glaeser et al. (2017), Fang et al. (2016)). This paper focuses on the supply side and is more related to previous work such as Haughwout et al. (2012) and Glaeser, Gyourko, and Saiz (2008). My analysis complements this literature by examining land allocation and illustrating how the public sector's involvement explains the oversupply of housing.

This paper also contributes to the literature on the supply of government-controlled resources (e.g., Asher and Novosad 2017, Levitt 1997). The paper most closely related to this one is Chen and Kung (2018). They show that Chinese firms linked to national political elites received discounts in land purchases, and provincial party secretaries who provided such discounts were more likely to be promoted. In contrast to corruption, this work provides evidence on market distortions by focusing on a different mechanism, i.e., economic growth incentives. Moreover, compared with reduced form analyses, the structural approach taken by this paper allows me to model city managers' decision-making process and evaluate their responses to different counterfactual scenarios. This paper is also closely related to Timmins (2002). The author finds that municipal managers in the western U.S. priced water below its marginal cost of production in order to increase voters' surplus, which is assumed to be critical for municipal managers' employment. In contrast, this paper models city managers' payoff as a function of career outcomes, which depends on incentives designed by the central government.

Methodologically, this paper draws on the literature of dynamic discrete choice models as used in Rust (1987) and Pakes (1986) and more recently adopted in Chen (2021), Hsiao (2021) and Schubert (2021). I combine the tools from single-agent dynamics with models from the career-concerns literature set off by Holmström (1999) and also Gibbons and Murphy (1992), Mathias Dewatripont (1999a), Mathias Dewatripont (1999b). I apply these methods to explain local politicians' behavior under the incentive contracts that current performance affects the future promotion probability. Lastly, this paper is related to the literature on monopolists' dynamic strategies. In contrast to Coase (1972), city managers in this paper supply more land at a lower price today in order to boost local economic growth rather than compete with future selves.

The rest of the paper proceeds as follows. Section 2 provides institutional details. Section 3 discusses data and motivating facts. Section 4 introduces the main model of city managers' decision making process. Section 5 describes how I estimate the model and reports the results. Section 6 presents counterfactual exercises. Finally, Section 7 concludes.

2 Background

This section provides institutional details on city managers' careers, an overview of how GDP is measured in China, and the development of the land and housing market.

2.1 City Managers' Career Incentives

Under the central government, China's administrative system has three layers: provincial level, prefectural level, and county level.[4] Above the county-level, there are 297 cities, which fall into one of the three hierarchical categories. Provincial-level cities include Beijing, Tianjin, Shanghai, and Chongqing. In addition, there are 15 sub-provincial level cities, usually province capitals or cities with economic and political importance. Half-level below these cities are prefecture-level cities.

Civil servants' political ranks usually mirror the hierarchy of their municipalities, although not always. According to The Civil Servant Law of China, civil servant leaders have ten possible posts, ranging from the national level, such as the president of China, to the township level, such as deputies of a town.[5]

[4]See the 2020 Statistical Yearbook, section 1-1 divisions of administrative areas in China http://www.stats.gov.cn/tjsj/ndsj/2020/indexeh.htm

[5]The law was initially passed in 2005 and took effect in 2006. It was revised in 2018 and took effect in 2019. My sample ends in 2017 and is therefore covered by the older version. Full text in English

The top two leaders in a city are the party secretary and the government mayor. Due to the ruling position of the Chinese Communist Party, the party secretary at each level is more senior than that of the leader of the government, with the CCP standing committee being the main source of power. Thus, I refer to party secretaries as city managers. There are four possible ranks for city managers: Politburo, province, deputy-province, and prefecture. When city managers leave the office, they may advance to a higher rank, move to a post with the same rank, be demoted, or resign. They shall retire if they reach the retirement age, which is usually 65 or 60. When they are promoted, the next positions are not necessarily the same post. For a prefecture-level city manager, the immediate higher rank is at the deputy province level, such as a deputy party secretary, a deputy governor of a province, or a deputy minister of the state council.

In terms of timing, city managers' promotion decisions are made at party meetings. According to the Constitution of the Communist Party of China, a party committee at any level must convene for at least two plenary meetings a year, and a party congress is supposed to be held every fifth year, which is usually at the end of that year. [6] One term for city managers is five years. However, they do not have to serve the entire term, and most of them stay for less than ten years.

Following a "one-level up" policy, city managers' promotion decisions are determined by the leadership at the level immediately above, with prefectural leaders supervised by the provincial officials and provincial leaders evaluated by members of the Politburo (Chen and Kung 2018). In addition, city managers are assessed at least annually by the higher administration. Promotion decisions are based on many factors, such as candidates' political loyalty, capability or achievement, educational qualifications, and working experience. As documented in the tournament literature, local economic measures such as GDP growth rates have been a key performance indicator (Wang, Zhang, and Zhou 2020;Maskin and Bai 2021;Li and Zhou 2005). For example, during each year's congress sessions, local governments report whether they have achieved the economic growth and other targets in the past year. Moreover, cities are usually ranked by their performance in economic growth, which is also viewed as a way to stimulate regional competition (Maskin, Qian, and Xu, 2000).

In addition, due to the historical reason of being a planned economy, making economic plans remains a routine practice at all levels of governments. Specifically, under each local government, the Development and Reform Commission is in charge of formulating economic and social development strategies and annual or long-term plans. In particular, the commission is responsible for putting forward annual aggregate targets, which are cited in local gov-

is available on the National Congress website `http://www.npc.gov.cn/zgrdw/englishnpc/Law/2007-12/13/content_1384101.htm`

[6] The Party Congress is different from the People's Congress, which is also once every five years.

ernments' annual work reports. Typically, the central government sets the national agenda at the end of a year for the following year, then provincial and prefectural levels announce their plans. Local governments would follow upper governments' guidelines as well as the local five-year economic plans. To pin down a proper target, local governments would meet with heads of local bureaus and districts, consult with academic experts and industry leaders, and seek advice from the congress and the consultative conference. It cannot be too low - governments want to give industries correct expectations and the confidence to invest. It also cannot be too high, as governments want to develop the economy steadily and smooth boom and bust cycles. When predicting next year's economic potential, current economic performance is viewed as the foundation. They may also consider the contribution of various industries and new technologies that might spur economic growth.

However, the emphasis on GDP growth was weakened after President Xi took office in 2013. For example, during a national party meeting on personnel and organization issues on June 28-29, 2013, President Xi stressed that "we should improve our way of evaluating officials' performance" and "should no longer evaluate the performance of officials simply against GDP growth." Instead, local governments should pay more attention to indicators such as welfare and ecological benefits.[7] Therefore, city managers are expected to respond and pay less attention to economic growth after 2012.

2.2 Measuring Gross Domestic Product

China established a centralized statistical system responsible for organizing and implementing statistical surveys at the national or local level. This system is comprised of statistical agencies in local governments at and above the county level and statistical stations at the township level.[8] The highest level statistical agency is the National Bureau of Statistics established under the State Council. Statistical agencies are under the dual leadership of governments at the same level and agencies at the higher level, with the latter primarily exercising leadership from the perspective of statistical operation. The local governments manage directors and deputy directors of local statistical bureaus at the corresponding levels with assistance from the statistical agencies of governments at higher levels. Therefore, local statistical bureaus collect data for higher-level bureaus and provide up-to-date statistical information and submit analysis reports for local governments.

[7] See Reuter's report https://www.reuters.com/article/us-china-economy-factbox/factbox-china-comment-xi-says-gdp-not-the-only-performance-metric-idUKBRE96007W20130701 and summaries by People's Daily http://cpc.people.com.cn/n/2013/0701/c363698-22031381.html

[8] The Official Statistical System of China: http://www.stats.gov.cn/english/nbs/200701/t20070104_59235.html

China introduced the Gross Domestic Product (GDP) accounting systems in the 1980s.[9] It is a core indicator of the national accounts and measures the final products at market prices produced by all resident units in the country during a certain period. In calculating GDP, corporate units are first divided into different industries according to their principal activities. Next, the value-added of each industry is calculated separately and then aggregated to the whole economy's GDP. Theoretically, there are three equivalent ways of calculating GDP: the production approach, the income approach, and the expenditure approach. These methods reflect the economy's production from different angles, and details are deferred to Appendix C.

Based on monthly data, the preliminary quarterly GDP is released about 15 days after the season, and the preliminary annual GDP is released around January 20th of the following year. The final verification data on quarterly and annual GDP are released in January, two years after the preliminary statistics. There may also be comprehensive revision if new basic information from the national economic census greatly impacts GDP data or when calculation methods and classification criteria change. GDP accounting mainly uses two sources of data. First is survey data collected by statistical agencies, and second is administrative records from government departments.

Since GDP measures new production but land revenues are generated from transferring the rights of using existing assets, the activities of leasing land do not add to GDP. However, construction activities that happened on the land count towards GDP. In particular, the value of apartments is included in GDP regardless of whether they are sold or not. Unsold homes, or developers' inventories, are new production in a given accounting period by definition. Moreover, GDP calculation adopts the accrual accounting method, where revenue or expenses are recorded when a transaction occurs, or liabilities are incurred rather than when payment is received or made.[10] As long as construction activities occur, developers do not have to pay workers in the same period in order for the value of production to be recognized as GDP in that period.

2.3 Land Market

Unlike many countries, the land usage right and the structure built on the land are sold separately in China. Moreover, the ownership of land is divided into state-owned urban land and collective-owned rural land. The legal system secures local governments' monopoly position in the urban land market and monopsony position in the rural market. For exam-

[9]Source: http://www.stats.gov.cn/english/PressRelease/202012/t20201231_1811928.html

[10]In contrast, cash basis refers to a major accounting method that recognizes revenues and expenses at the time cash is received or paid out.

ple, any firm or individual who wants to build on a parcel of urban land has to obtain a leasehold allocated by local governments and valid for a certain period. Under current law, industrial land for building industrial and manufacturing facilities can be leased for 30 years, commercial land for commercial and business facilities has leasehold terms of 40 years, and the leaseholds for residential land for residential properties expire in 70 years (Liu and Xiong 2020).

The allocation process has experienced dramatic reforms. In the 1990s, while public auctions were available, the land was allocated mainly by negotiations between developers and governments. The hidden and opaque nature of this process gave rise to wild corruptions. As a result, in May 2002, the Ministry of Land and Resources banned negotiated sales. The No.11 regulation required all residential and commercial land leaseholds to be sold via public auctions after July 2002. Then in March 2004, the requirement was further institutionalized in Decree 71, and all land parcels have to be leased by public auctions (Wang and Yang 2021;Deng, Gyourko, and Wu 2014).

Several local institutions are involved in the allocation process. First, as documented in (Cai, Henderson, and Zhang, 2013), the local planning bureau is responsible for long-term land-use planning. Then in each year, the local government organizes a land-use allocation committee that determines the details of land to be leased, such as the floor-to-area ratio and the sales sequence. Finally, after these decisions are made, the local land bureau executes, such as choosing auction types and holding the auction.

For public auctions, two formats are mostly adopted: English auctions and two-stage auctions. The auctions are announced 20 working days in advance for both types, and land details are posted. English auctions are standard. Potential bidders enter simultaneously at the prescribed time and locality. They participate in open competition and submit ascending bids with the required minimum increment. The highest price offer determines the land user, and the winner pays his/her last bid.

In contrast, in a two-stage auction, bidders enter sequentially, and the land user is determined according to the price offered at the closing time of the listing time limit or the result of on-the-spot price competition. The first stage usually lasts for ten working days. After issuing a notice of listing, the land department draws up the transaction terms of granting land plots in the time limit prescribed by the notice. Then the department posts them in a public land transaction house, receives the offer applications of the bidders, and renews the listed prices accordingly, but bidder identities are not revealed. At the end of the first stage, If more than one bidder is still willing to raise the price, the auction converts to an English auction on the spot. Another format, sealed bids, is also allowed by law but is rarely used.[11]

[11]Source: 2018 China Land and Resources Statistical Yearbook

Although not private monopolists, local governments still want to maximize land profits, and this incentive is strengthened by two fiscal reforms in the 1990s (Liu and Xiong 2020). First, the 1994 tax-sharing reform reduced local governments' share of the total budgetary revenue. Second, the 1995 Budget Law required local governments to maintain balanced budgets except in some instances and prohibited them from obtaining external financing. As a result, non-budgetary incomes such as land revenues become essential sources of funding.

In general, local governments can obtain "new" land by assembling urban land (brown-field) or acquiring rural land from farmers (green-field). Under collective ownership, the use of rural land is designated mainly for agricultural purposes. Other uses may include villages' housing, enterprises, and infrastructure. In order to be developed for construction or other non-agricultural uses, these land parcels have to be first converted from collective-owned to state-owned, and the land value-added accrues to local governments (Zhang and Xu 2016). For both types of land, there may be government expenditures on clearing and basic infrastructure prior to the land transfer. There may also be a small administration cost for land assessment and auctions. For land acquired from farmers, there is also compensation cost according to the original purposes of the land requisitioned. By China's 1998 Land Administration Law, it has four components: (1) the compensation for the land itself; (2) resettlement allowances or relocation cost for farmers who used to live or work on the land; (3) compensation for above-ground buildings and other attached objects; (4) compensation for young crops. The first two are calculated based on a bench market price and a multiplier. Local governments have flexibility in setting the compensation for structure and crops according to local economic conditions. Also, the sum of land compensation and resettlement fees rarely exceed 30 times the average annual output value (Zhang and Lu 2011).

2.4 Housing Market

Commercial housing emerged in China only in recent decades, and the central and local governments heavily influence the market. Prior to the 1980s, working units assigned housing to employees as an in-kind benefit, based on factors such as tenure and the size of the household. Then starting from 1988, private firms were allowed to purchase land-use rights, and the housing system was ready for privatization in 1994. As a result, homes became commodities, and employees could purchase the full or partial property rights of their assigned apartments at subsidized rates (Fang et al. 2016). Since then, the housing market has grown rapidly and become a pillar industry of China's economy.

Since land is one of the most crucial inputs for real estate, local governments directly affect housing construction activities by changing the supply of available land. Moreover, as banks are one of the developers' primary funding sources, the development of the housing market corresponds to years with low-interest rates and easy monetary policies. Typical examples include the periods after the 1997 Asian Financial Crisis and the post-2008 global economic crisis. In the first example, China's central bank, the People's Bank of China, lowered mortgage interests rates five times, broadened the scope of development loads, and allowed presales by developers (Fang et al. 2016). After 2008, interests rates were set barely above inflation, and the 4 trillion Yuan (586 billion USD) stimulus package was injected into the economy partly through the housing market. In contrast, interest rates and down payment requirements would be raised when housing prices rose too fast, and the construction booms led to concerns of forming a bubble. Governments can also restrict the quantity, i.e., the number of apartments that each household is allowed to purchase.

Furthermore, due to the residential construction sector's history of being entirely state-owned, several leading developers in today's housing market are still SOEs or partly held by governments. For example, the Poly Real Estate Group is a large state-owned real estate enterprise and has a 2.3% share of the whole nation's market, with sales revenue reaching 10.9 billion USD in 2012. It was founded in 1992 and is controlled by China Poly Group. Also founded in 1992, Greenland Group is a large state-holding enterprise in Shanghai and was ranked one of the top three real estate enterprises in 2011. As another example, China State Construction Engineering Corporation is a leading real estate enterprise founded in 1982 and is directly controlled by the central government. The company generated 8.33 billion USD of revenues in 2012 and was listed as one of the Financial Times' Global 500.[12]

3 Data and Suggestive Evidence

In this section, first, I explain how I collect the data. Then I present evidence on political cycles and show that land market equilibrium follows a similar pattern.

3.1 Combining City and City Manager Data

I construct a manager-city-year level panel data from 2003 to 2017. The dataset covers 295 cities at the provincial or the prefectural level, only missing the Sansha city in Hainan Province and the Nagqu city in Tibet. Primary sources include two yearbooks collected by third-party data vendors the China Economic Information Center (CEIC) and the China Real Estate Information (CREI). The first one is the Statistical Yearbook published by each Municipal Bureau of Statistics around July every year based on data from the previous year.

[12]Source: IBIS World Industry Report 7210A, Residential Real Estate in China, March 2019 version.

It documents key social and economic development indicators, such as the city's administrative area, the actual GDP growth rate, population, fiscal revenue, and expenditure.

The second one is the China Land and Resources Statistical Yearbooks, published by the Ministry of Land and Resources (now the Ministry of Natural Resources). It reports the total amount of actual revenues received by city governments by granting state-owned land leases to a unit or an individual. It also reports the corresponding total area of land transacted. The reported revenue and area are the total of three common transaction forms: bidding, auction, and listing. Therefore, the analysis does not distinguish the methods of public auctions.

As yearbooks only record the realized GDP growth rates, I manually collected GDP growth targets to measure city managers' performance. These data are publicly available from each city's Report on the Work of the Government, delivered by local governments at annual sessions of People's Congress.

The last dataset is the Chinese Local Government Officials Database maintained by a third-party Chinese Research Data Services Platform (CNRDS). CNRDS tracks detailed information on government officials at the province, prefecture, and county levels, starting as early as the 1940s and ending in December 2018. For each individual that ever served as a city manager (party secretary), this dataset lists the individual's name, the starting and ending year-month of his/her term, and most importantly, a unique person identifier. Thus, when two city managers share the same name, it allows me to tell whether that one individual moved to another city or there are two distinct individuals. It also contains demographics such as ethnicity, gender, birthplace, birth date, year of joining the Communist party, and the highest education degree.

Nevertheless, one essential piece of information is city managers' career outcomes. Therefore, I augment the analysis by manually collecting city managers' resumes from public resources, such as the Chinese party and government leaders database launched by People's Daily in 2012.[13] People's Daily is one of the largest newspaper groups in China. It is an official publication of the Central Committee of the Chinese Communist Party. I also supplement the database with Baidu Baike, an online encyclopedia similar to Wikipedia. In rare cases, information from three resources differs, I follow the database from People's Daily. Finally, to code a city manager's career outcome, I compare his/her political rank when first assigned to the city manager office with the rank of the immediate next job after leaving the city manager position. If the next job has a higher rank, then the outcome is coded as "promotion".

[13] The launch of the database: http://en.people.cn/90785/8000338.html and the link for the database: https://ldzl.people.com.cn/dfzlk/front/firstPage.htm

To match the data on city characteristics such as GDP growth rate, I reshape the manager-city level data to the manager-city-year level. That is, I assign the city manager to each city-year observation. If two individuals served in the same city during the same year, the one that stayed longer in that year is labeled as the city manager. For example, a manager may leave the office in February, and a successor is in charge for the rest of the year. Then the successor is coded as the city manager for that year. Moreover, for managers who moved early in a year, such as February 2013, I interpret the *decision* as being made based on his/her performance in previous years. Thus, I only use data before 2013 to estimate the advancing function.

3.2 Describing Political Environment

The dataset spans 15 years and covers 295 provincial-level and prefecture-level cities. As reported in Table 1, I do not have a balanced panel due to missing data. Since one term for city managers is five years, and they do not have to serve the entire length, there were many movements during the sample period. Thus, it is common to observe more than one manager in a city across different years. As a result, there are 1,216 unique managers, more than the number of distinct cities (295). Moreover, an individual may be moved to serve as city manager in a different city, such as Jinhua City to Wenzhou City. Therefore, the number of unique manager-city pairs (1,392) is slightly larger than that of unique managers (1,216).

Table 1: Dataset Overview

Total observations	4,270
Unique number of cities	295
Unique number of years	15
Unique number of managers	1,216
Unique number of manager-city	1,392

Note: This table provides an overview of the dataset. It covers 295 provincial-level and prefecture-level cities and spans 15 years. Due to the change of city managers, the unique number of managers is larger than the number of distinct cities. In addition, a few city managers were moved to serve as city managers in different cities, resulting in the number of manager-city pairs being more than the number of unique managers.

This dataset covers President Hu from 2003 to 2012 and President Xi starting from 2013. Table 2 reports the summary statistics on city managers' tenures by president. Overall, during Hu's time, city managers stayed for 3.97 years on average, which is higher than the average tenure of 3.09 years during Xi's time. In the full sample, the average stay is 3.67

years.[14] Overall, more than 86% of city managers stayed in the same position for less than five years, and only one person had tenure for more than ten years. Table B2 in the Appendix displays the detailed frequency by tenure.

Table 2: Statistics on City Manager Tenure (year)

President	N	Mean	p50	Min	Max
Hu (2003-2012)	910	3.97	4	1	11
Xi (2013-2017)	482	3.09	3	1	8
Total	1,392	3.67	4	1	11

Note: This table reports the summary statistics on city managers' tenure by president. Overall, the average stay is 3.67 years, less than a full term of five years. However, the tenure was longer during Hu's presidency, which is 3.97 years, than the average of 3.09 years during Xi's time.

As discussed in Section 2.1, promotion decisions for city managers are usually made at party meetings. Moreover, party congresses at all levels are held every five years, during which members of the party committees are elected. The highest level congress, the National Congress, has been held in October or November since 1987. This dataset covers the 17$^{\text{th}}$ through the 19$^{\text{th}}$ congresses, with the congress years of 2007, 2012, and 2017. Since the elections have a five-year cycle, it should be reflected in the data. Indeed, Figure 1 shows that the cycles of city managers' promotion probabilities are consistent with the timing of party congresses. Specifically, it plots the average probability of city managers being promoted in each calendar year across the country. In congress years, the chance of advancing exceeded 0.15 and reached 0.25 in 2007, while in other years, the probability can be below 0.05.

Furthermore, although city managers may be moved at any time, they are more likely to leave the office at the end of a year or early next year, especially for movements around congress years. For more details, Table B1 in the Appendix tabulates the months in which city managers left the office. Thus, city managers are aware of the promotion cycles and know that performance throughout the year counts.

3.3 Connecting with Economic Outcomes

Similar to promotion, land market equilibrium also experiences cycles. For example, Figure 2 plots the area of land being leased through public auctions, averaging across cities during years relative to party congresses. 0 represents the congress years of 2007, 2012, and 2017; -1 means the year before a congress year, such as 2006, 2011, and 2016. The plot shows that

[14] This statistic is similar to findings in the literature. For example, Wang, Zhang, and Zhou (2020) documents that the average term was around 3.7 years from 2000 to 2011.

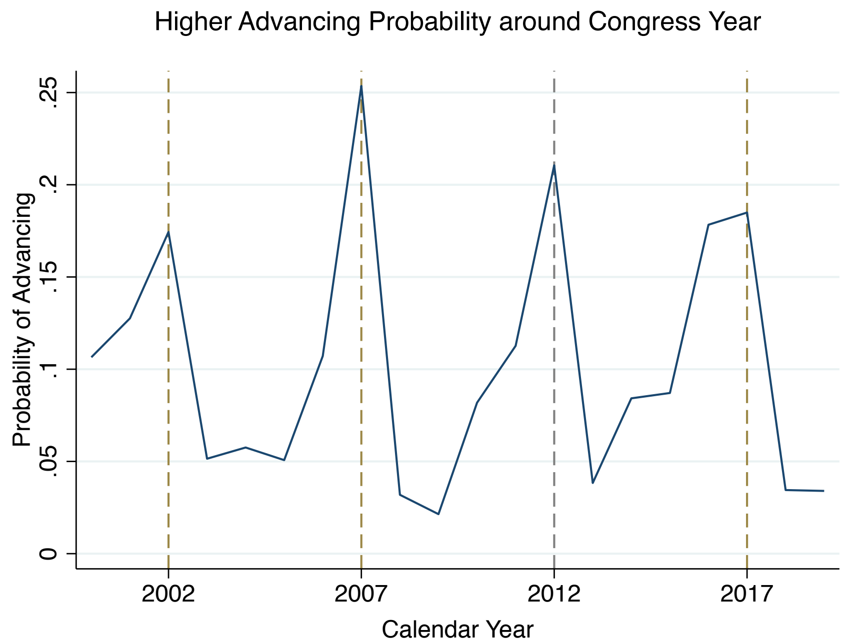

Figure 1: This figure plots the average probability of city managers being promoted each year. The cycles of promotion probability are consistent with the timing of party congresses.

land lease sales also experienced cycles: most land parcels were sold during congress years, and less if further away. More importantly, the cycle mirrors that of promotion, suggesting that political and economic outcomes may be correlated.

While land sales show that the benefits of leasing land are in general higher around congress years, Figure 3 illustrates that the marginal incentives are higher for cities that are on the border of achieving economic goals. Specifically, the binscatter plots the log of the land area leased via public auctions versus the deviation of the actual GDP growth rates from the pre-determined GDP growth rate targets. For example, 5 on the X-axis means the actual GDP growth rate is 5 percentage points higher than the growth rate target set at the beginning of that year. City fixed effects are removed. The plot exhibits an S-shape. When cities are around the growth targets, land sales decrease as they get close to the targets. The relationship is flatter when cities are further away from targets. Although the relationship is a purely correlation, it is consistent with the hypotheses that cities near GDP growth targets have stronger incentives to boost the economy, in order to hit the targets. In contrast, cities that greatly exceed the growth thresholds do not need to stimulate the economy, and cities far below the targets may find extra land sales are not worthwhile.

Lastly, Figure 4 sheds light on how GDP growth targets are determined by linking the new targets to the previous year's performance. City fixed effects are removed. In general,

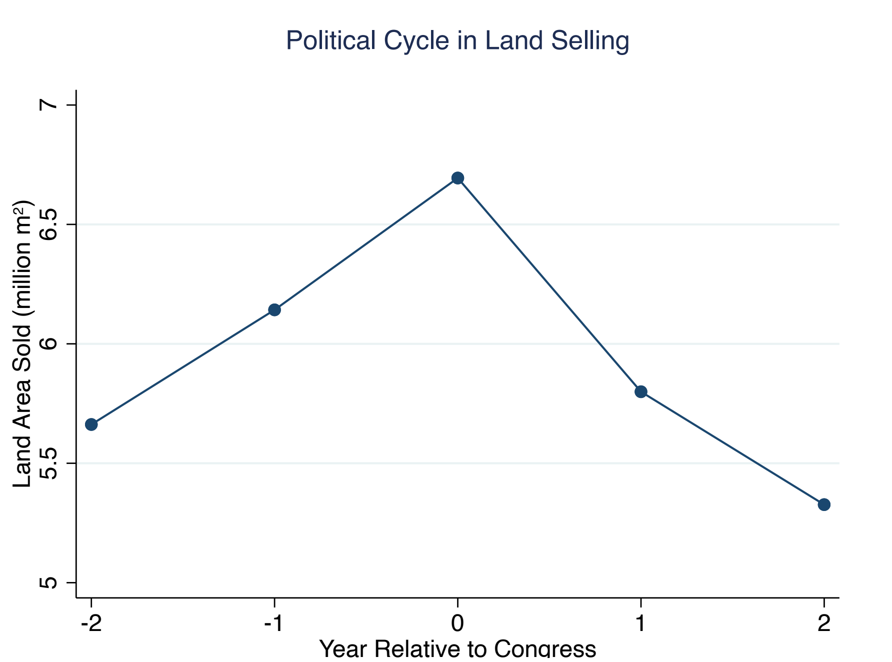

Figure 2: This figure plots the average land area leased at the city level during years relative to party congresses. For example, 0 represents the congress years of 2007, 2012, and 2017. It shows that land lease sales also experienced cycles: most land parcels were sold during congress years, and less if further away. More importantly, the cycle mirrors that of promotion.

cities that have higher GDP growth rates also have higher targets. Moreover, the new targets are higher when cities outperform last year's growth targets more. The slope is also slightly steeper for those above the targets. Nevertheless, these are all correlations, but they help understand the relationship between the actual growth and the targets.

4 Land Supply Model

This section presents a framework to rationalize city managers' decisions on land supply. Why do we need such a model? First, managers' relative weights on promotion versus profits cannot be directly observed but are revealed by their actions. Second, I can perform counterfactual analyses and evaluate market equilibrium under different scenarios after estimating the structural model.

The model highlights the trade-offs of providing more land: on the one hand, managers have to accept a lower price due to a downward sloping demand curve. On the other hand, since land is a key input for production, a higher GDP growth rate helps the city manager hit the predetermined target and increase his promotion probability.

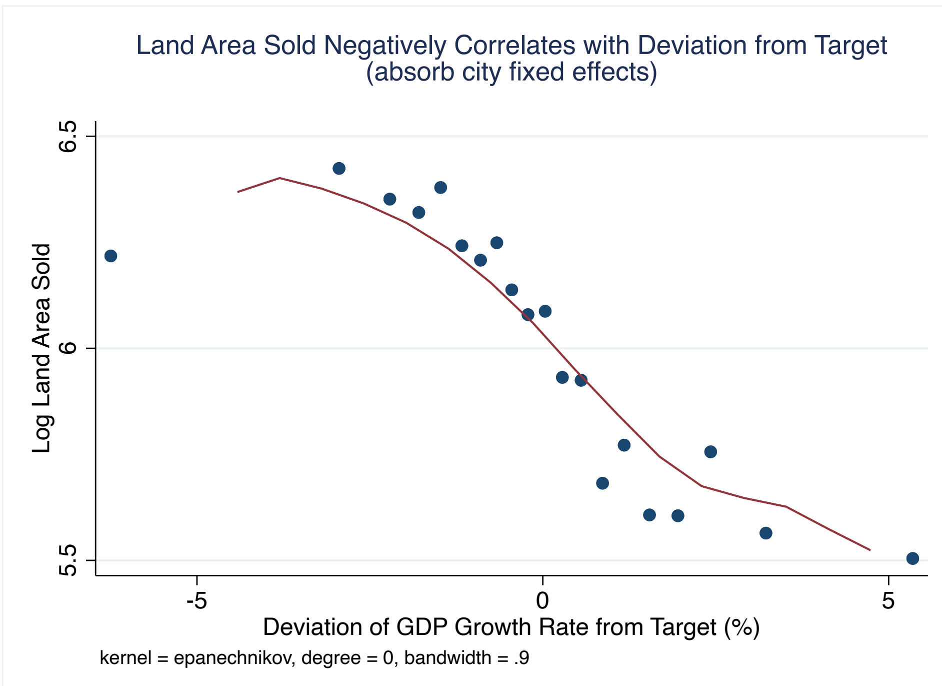

Figure 3: This figure plots the log of the land area leased via public auctions versus the deviation of the actual GDP growth rates from the pre-determined GDP growth rate targets. City fixed effects are removed. When cities are around the growth targets, land sales decrease as they get close to the targets. The relationship is flatter when cities are further away from targets.

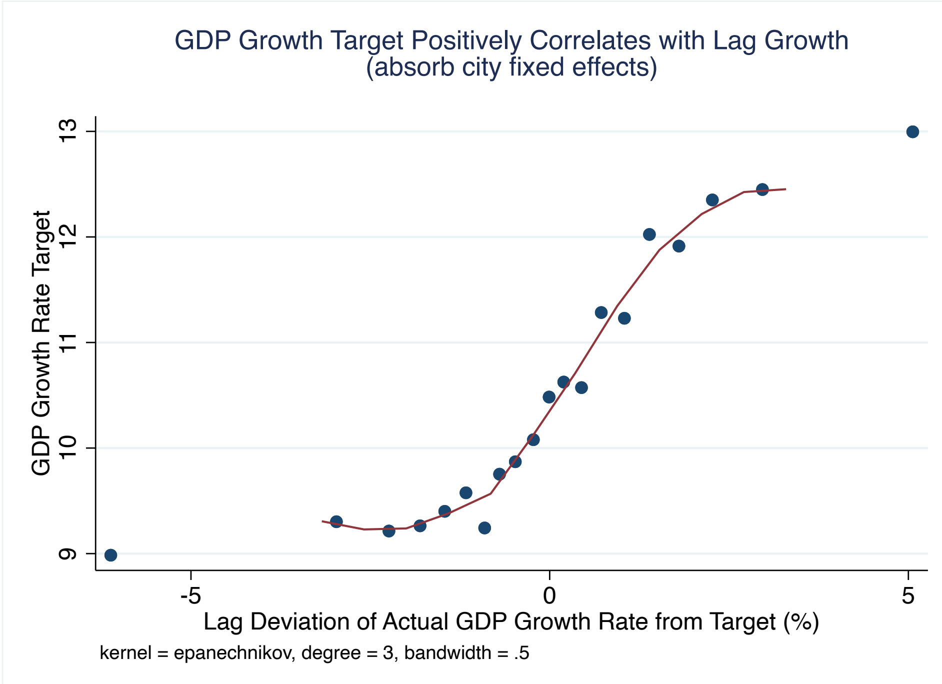

Figure 4: This figure plots the GDP growth rate targets versus the previous year's deviation of actual GDP growth rates from that year's growth targets. City fixed effects are removed. The new growth targets positively correlate with the past year's performance relative to targets.

In addition to the static trade-off, a forward-looking city manager also considers the impacts of today's actions on the future self through three channels. Being able to hit the GDP growth target today contributes to a better economic performance history, which improves his chance of being promoted tomorrow. Moreover, today's higher GDP growth rate provides a better foundation for economic development, leading to higher GDP growth tomorrow and higher willingness to pay for the land. However, since future GDP growth targets increase with the current GDP growth rate, boosting the economy too much would make future targets harder to achieve. City managers would want to over-supply land due to the first two incentives, but under-supply because of the third incentive.[15]

I first introduce state variables and their transition processes. Then I describe city managers' flow payoff. Finally, I explain city managers' optimization problems.

4.1 State Transitions

I model city managers' optimization problem as infinite-horizon, where one period can be thought as one year. The choice variable is the amount of land to lease Q_{jit} by manager j

[15]One potential dynamics involved but ignored in the model is the impacts on the total land stock.

in city i and year t. The timing is as follows.

At the beginning of each period, the agent observes the state variable S_{jit}, which has four components: lag GDP growth rate $G_{ji,t-1}$, calendar year t, GDP growth target G^*_{jit}, and the average probability of hitting the target in previous years $\overline{H}_{ji,t-1}$. Note that city managers' characteristics enter the state variable through $\overline{H}_{ji,t-1}$, which is reset for different person-city and takes care of the change of city managers. Except for the calendar year, which evolves exogenously, the other three state variables are endogenous and can be affected by choice of land supply.

After observing the state, during the year, city managers choose the optimal land supply $Q(S_{jit}) = Q(G_{ji,t-1}, t, G^*_{jit}, \overline{H}_{ji,t-1})$. City managers receive a static payoff $\pi(Q_{jit}(S_{jit}), S_{jit})$. At the end of the year, shocks in the economy realize, generating the actual GDP growth rate G_{jit}. The history economic performance $\overline{H}_{ji,t-1}$ is updated, and the growth target for the next period G^*_{jit} is set. Specifically, the states evolve to the next period as described below.

4.1.1 GDP Growth Rate Evolution

The GDP growth rate G_{jit} in city i and year t depends on the lag GDP growth rate $G_{ji,t-1}$ and current years' land area being leased Q_{jit}. Random shocks follow a normal distribution $\varepsilon^G_{jit} \sim \mathcal{N}(0, \sigma^2_G)$ are unobserved by both city managers and econometricians. I also include city dummies γ_i and year dummies γ_t to account for unobservables that do not vary for a given city or over time.

$$G_{jit} = \gamma_0 + \underbrace{\gamma^G G_{ji,t-1}}_{\text{lag growth}} + \underbrace{\gamma^Q \log(Q_{jit})}_{\text{land}} + \gamma_i + \gamma_t + \varepsilon^G_{jit} \tag{4.1}$$

Although city managers do not observe the actual growth shock ε^G_{jit} at the time of making land supply decisions, they know its distribution and therefore the mean $\mathbb{E}[\varepsilon^G_{jit}] = 0$. Thus, for a given choice of Q_{jit}, the expectation of current year's GDP growth rate $\mathbb{E}[G_{jit}]$ rather than the actual G_{jit} enters into their objective function:

$$\mathbb{E}[G_{jit}] = \gamma_0 + \gamma^G G_{ji,t-1} + \gamma^Q \log(Q_{jit})$$

I observe the lag growth $G_{ji,t-1}$ and the equilibrium land area leased Q_{jit}. Parameters to be estimated are the reduced form coefficients γ^G and γ^Q.

4.1.2 Updating Average Probability of Hitting Targets

Let A_{jit} be a dummy variable that equals 1 if the manager advances politically at the end of the year and 0 if not. Since the party congress is every five years, I assume that the central government reviews a city manager's performance history. However, I allow more recent years to be more critical. For tractability, if a manager stays in the same position, the average probability of hitting targets is updated as the average of his past performance $\overline{H}_{ji,t-1}$ and whether the city hits the target or not this year H_{jit}. If the manager was newly appointed to the city, the current year's performance is the only history:

$$\overline{H}_{jit} = \begin{cases} \frac{1}{2}\left(\overline{H}_{ji,t-1} + H_{jit}\right) & \text{if } j(i,t) = j(i,t-1) \\ H_{jit} & \text{if } j(i,t) \neq j(i,t-1) \end{cases} \tag{4.2}$$

4.1.3 GDP Growth Target Transition

Tomorrow's GDP growth target is modeled as a function of today's target G^*_{jit} and today's performance. Specifically, it includes whether the city hits the target today H_{jit} and the deviation of actual GDP growth from today's target Dev_{jit}. Random shocks follow a normal distribution $\varepsilon^{G^*}_{jit} \sim \mathcal{N}(0, \sigma^2_{G^*})$. City dummies and year dummies are included to take care of unobserved but fixed effects:

$$G^*_{i,t+1} = \nu_0 + \underbrace{\nu_{GT} G^*_{jit}}_{\text{lag target}} + \underbrace{\nu_H \mathrm{H}_{jit} + \nu_{HD} \mathrm{H}_{jit}\mathrm{Dev}_{jit} + \nu_{MD}(1 - \mathrm{H}_{jit})\mathrm{Dev}_{jit}}_{\text{lag hit and deviation}} + \nu_i + \nu_{t+1} + \varepsilon^{G^*}_{i,t+1}$$

The deviation from target Dev_{jit} is simply the difference between the actual GDP growth rate realized at the end of each year and the GDP growth rate target, which is announced at the beginning of a year. Related, the dummy variables for hitting the target H_{jit} equals 1 if the actual GDP growth rate passes the threshold:

$$\begin{aligned} \mathrm{Dev}_{jit} &= G_{jit} - G^*_{jit} \\ \mathrm{H}_{jit} &= \mathbb{I}(G_{jit} \geq G^*_{jit}) \end{aligned}$$

Note I allow both the *slope* and the level of growth target to depend on the performance variables Dev_{jit} and H_{jit}. Therefore, there is a jump when H_{jit} shifts from 0 to 1, and the function is non-differentiable at this point. Also, both econometricians and city managers do not observe the random shock $\varepsilon^{G^*}_{jit}$. However, its distribution is known.

I observe the actual growth $G_{ji,t-1}$ and the corresponding target $G^*_{ji,t-1}$, from which I calculate the deviation Dev_{jit} and the hit dummy H_{jit}. Parameters to be estimated are the reduced form coefficients ν_{GT}, ν_H, ν_{HD}, and ν_{MD}.

4.2 Per Period Payoff

City managers' utility is derived from two sources. First is $\mathbb{P}(A_{jit} = 1)$, the probability of being promoted at the end of the year. Second is the expected profits from selling land leaseholds. Thus, the flow payoff for manager j in city i and year t is:

$$\pi(Q(S_{jit}), S_{jit}) = \omega \underbrace{\mathbb{P}(A_{jit} = 1)}_{\text{prob. advancing}} + \underbrace{(\mathbb{E}[P_{jit}] - MC_{jit})\ Q_{jit}}_{\text{expected profit}} \tag{4.3}$$

where A_{jit} is a dummy variable. It equals 1 if the manager gets promoted at the end of the year. P_{jit} is the average land price. It is in expectation as the land market shock has not been realized yet. MC_{jit} is the local government's marginal cost for leasing land. Assumptions on the specific functional forms are described below.

I normalize city managers' weight on expected profits to one, so ω represents the relative weight on the probability of advancing politically. This weight parameter will be inferred by fitting data with the model's prediction on optimal land supply.

4.2.1 Probability of Advancing

I assume that the error for being promoted follows the standard normal distribution, with the cumulative distribution function denoted as Φ. Thus, the probability of advancing follows a probit model:

$$\mathbb{P}(A_{jit} = 1) = \Phi(\alpha_{1t} + \underbrace{\alpha_{2t} \cdot \mathbb{E}[\overline{H}_{jit}]}_{\text{avg. target hitting}} + \alpha_i)$$

where $\overline{H}_{jit}$ is manager j's average probability of hitting targets in city i by the end of year t, as in Equation (4.2). It is in expectation as today's performance dummy H_{jit} has not been realized yet.

For pre-determined growth targets, H_{jit} depends on the expected growth, which in turn is affected by the amount of land sold through Equation (4.1). Thus, city managers can influence $\mathbb{E}[\overline{H}_{jit}]$ by supplying more land, and the model captures the economic performance channel of promotion.

As seen in Figure 1, the probability of promotion varies by year and is usually higher in congress years. Therefore, the model captures the difference in the levels of promotion probability by including dummy variables α_{1t}. It also allows the importance of economic performance to vary by time periods, which is summarized in the interaction terms α_{2t}. I also control for city dummies α_i to reflect that cities may have different political importance.

Econometricians observe the actual outcomes of the promotion dummy A_{jit} and the dummy for hitting GDP growth rate targets in each year H_{jit}. The parameters of interests are time coefficients α_{1t} and the marginal benefits of hitting growth targets on average as perceived by city managers α_{2t}.

4.2.2 Aggregate Land Demand

The average land price P_{jit} is a function of land quantity as well as the general economic condition in a city, i.e., the GDP growth rate. There are also city dummies β_i and year dummies β_t:

$$P_{jit} = \beta_0 + \underbrace{\beta^Q \log(Q_{jit})}_{\text{land}} + \underbrace{\beta^G G_{jit}}_{\text{GDP growth}} + \beta_i + \beta_t + \varepsilon^P_{jit}$$

Econometricians observe the panel of land price P_{jit}, land quantity Q_{jit} and GDP growth rates G_{jit}. The demand shock ε^P_{jit} is unobserved. City managers also only know its distribution $\varepsilon^P_{jit} \sim \mathcal{N}(0, \sigma^2_P)$. Parameters to be estimated are the reduced form aggregate land demand elasticities $\left(\beta^Q, \beta^G\right)$.

4.2.3 Marginal Land Cost

Local governments' cost of leasing an additional unit of land is parameterized as:

$$MC_{jit} = c_0 + c_1 \cdot \text{population density}_{jit} + c_2 \cdot \mathbb{I}(2009 \leq t \leq 2012) \tag{4.4}$$

As discussed in Section 2.3, typical marginal costs include farmers' resettlement costs and compensations for land and structures. Since I do not directly observe these costs, I model it as a function of population density. I also include a dummy for the four years after the 2008 financial crisis when the macro policies were more friendly for the land and housing market. The marginal cost parameters c_0, c_1, and c_2 will be estimated by fitting the model prediction with data.

4.3 Objective Function

As discussed in the previous two sections, city managers' information set is comprised of two parts. One is the state variables, including lag growth $G_{ji,t-1}$, current growth target G^*_{jit}, lag average probability of hitting targets $\overline{H}_{ji,t-1}$ and calendar year t. The second part includes marginal cost parameters and the parameters governing the distribution of several shocks: σ^2_G for growth shocks, $\sigma^2_{G^*}$ for growth target shocks, σ^2_P for land demand shocks.

A myopic city manager only cares about the current period. Thus, the problem is to maximize the static payoff as in Equation (4.3) by choosing the amount of land to lease:

$$\max_{Q(S_{jit})} \pi(Q(S_{jit}), S_{jit}) = \max_{Q(S_{jit})} \omega \underbrace{\mathbb{P}(A_{jit} = 1)}_{\text{prob. advancing}} + \underbrace{(\mathbb{E}[P_{jit}] - MC_{jit})\ Q_{jit}}_{\text{expected profit}} \tag{4.5}$$

However, if the agent is forward-looking, he/she also cares about future land profits and the probability of being promoted in the future. Thus, a continuation value enters into the value function, and the Bellman equation is:

$$V(S_{jit}) = \max_{Q(S_{jit})} \underbrace{\pi(Q(S_{jit}), S_{jit})}_{\text{payoff}} + \underbrace{\rho \int_s V(S_{ji,t+1})\ dF(S_{ji,t+1}|S_{jit}, Q(S_{jit}))}_{\text{continuation value}}$$

where ρ is the discount factor, and F denotes the transition probability of state variables.

More explicitly, the value function takes state variables as inputs. Also, city managers' control variable $Q(S_{jit})$ affects the transition probability of endogenous state variables:

$$\begin{aligned}
&V(G_{ji,t-1}, t, G^*_{jit}, \overline{H}_{ji,t-1}) \\
=& \max_{Q(S_{jit})} \omega\ \mathbb{P}(A_{jit} = 1) + (\mathbb{E}[P_{jit}] - MC_{jit})\ Q_{jit} \\
&+ \rho \int_G \int_{G^*} \int_{\overline{H}} V(G_{jit}, t+1, G^*_{i,t+1}, \overline{H}_{jit}) \\
&dF(\overline{H}_t|G_t, G^*_t, \overline{H}_{t-1})\ dF(G^*_{t+1}|G_t, t, G^*_t)\ dF(G_t|G_{t-1}, t, Q(S_t))
\end{aligned}$$

That is, today's land supply affects today's GDP growth rate, which then affects both tomorrow's GDP growth rate target and actual GDP growth rate. The realization of the GDP growth rate also determines how the average probability of hitting targets will be updated.

It is worthwhile to note that the dynamic first-order condition has two parts. First is the derivative of the static payoff with respect to the choice variable, and second is the derivative of the continuation value.

$$\begin{aligned}
&\frac{\partial \pi(Q(S_{jit}), S_{jit})}{\partial Q(S_{jit})} + \rho \cdot \frac{\partial\ CV(Q(S_{jit}), S_{jit})}{\partial Q(S_{jit})} \\
&= \omega \frac{\partial \mathbb{P}(A_{jit} = 1)}{\partial Q(S_{jit})} + \underbrace{\frac{\partial(\mathbb{E}[P_{jit}] \cdot Q_{jit}(S_{jit}))}{\partial Q(S_{jit})} - MC_{jit}}_{\text{static monopolist}} + \rho \cdot \frac{\partial\ CV(Q(S_{jit}), S_{jit})}{\partial Q(S_{jit})}
\end{aligned} \tag{4.6}$$

Compared with a forward-looking monopolist, city managers also consider the marginal benefits on the probability of promotion, which is the first term in the dynamic first-order condition.

5 Estimation and Results

The structural model is estimated by two stages. In the first stage, I estimate the static parameters $\theta_1 = \{\alpha's, \beta's, \gamma's, \nu's\}$ from four equations: the advancing function, inverse land demand, GDP growth evolution, and the transition of GDP growth rate target. Given $\hat{\theta}_1$, I estimate the dynamic parameters $\theta_2 = \{\omega's, c's\}$, which are the weights on political incentives relative to expected land profits, and marginal land cost parameters.

I also restrict the sample to cities with observations on all state variables for seven or more years. The reasons are two-fold. First, to compute the optimal land supply as predicted by the model, I need to observe all state variables for that manager-city-year. Second, I need a long enough panel to control for city fixed effects. This procedure leaves us with 213 cities and 3,195 observations, which is 75% of the data.

5.1 First Stage

In this section, I explain how I estimate the reduced form parameters for GDP growth evolution ($\gamma's$), inverse land demand ($\beta's$), the advancing function ($\alpha's$) and the transition of GDP growth rate target ($\nu's$).

5.1.1 GDP Growth

Recall GDP growth rate evolution as in Equation (4.1):

$$G_{jit} = \gamma_0 + \underbrace{\gamma^G G_{ji,t-1}}_{\text{lag growth}} + \underbrace{\gamma^Q \log(Q_{jit})}_{\text{land}} + \gamma_i + \gamma_t + \varepsilon^G_{jit}$$

One potential omitted variable is city managers' ability and ambition. Higher ability may be correlated with a higher GDP growth rate in both last year and this year. Another unobservable are demand shocks in local land markets. A positive shock, such as a city suddenly becoming famous for tourism, may lead to higher equilibrium land quantity and correlate with higher GDP growth rates. I control for city fixed effects and time fixed effects and estimate the equation using two-stage least squares to alleviate these problems.

To identify γ^G, I exploit variations in common regional shocks, which is orthogonal to an individual city manager's ability. Specifically, I use the lag value of the average GDP growth of neighboring cities, denoted as $NG_{ji,t-1}$. Neighbor cities are defined as those with shared borders.

To identify the impacts of land sold on cities' economic performance γ^Q, I need variations in the land market equilibrium that is unrelated to demand shocks. Therefore, I construct a variable $\text{DeficitShare}_{jit}$ to measure local governments' propensity to sell land:

$$\text{DeficitShare}_{jit} = \frac{\text{Fiscal Expenditure}_{jit} - \text{Fiscal Revenue}_{jit}}{\text{GDP}_{jit}}$$

which is the share of local government's fiscal deficit out of the city's GDP level. The idea is that tax revenues and land revenues are the two main sources of local governments' income. However, tax revenues are more likely to be constrained by legal procedures, budgetary planning, and the contract with the central government. In contrast, local governments have more freedom to lease land, which can also be implemented flexibly. Therefore, places that run a larger deficit, normalized by GDP level, would be more likely to resort to land sales to collect money.

The moment restrictions are:

$$\begin{gathered}\mathbb{E}[\varepsilon^G_{jit}\ \text{IV}_{jit}] = 0 \\ \text{Instruments: IV}_{jit}\ \in \{\text{DeficitShare}_{jit},\ NG_{ji,t-1}\}\end{gathered}$$

Table 3 reports the estimates from the reduced form and the corresponding first-stage regressions. In all specifications, I include city FEs and year FEs. As expected, higher land supply and higher lag GDP growth rates contribute to higher GDP growth today. The instruments are strong, with F-statistics larger than 30.

Table 3: GDP Growth Evolution

	(1)	(2)	(3)	(4)
	OLS	2SLS	First Stage OLS	
	GDP Growth	GDP Growth	Log Land Area Sold	Lag GDP Growth
Log Land Area Sold	0.266***	2.330***		
	(0.0779)	(0.733)		
Lag GDP Growth	0.524***	0.597***		
	(0.0158)	(0.0437)		
Fiscal Deficit/GDP			1.823***	-0.605
			(0.299)	(1.194)
Lag Neighbors' GDP Growth			0.0360***	0.825***
			(0.00493)	(0.0197)
Constant	5.084***	1.539	1.029***	-0.251
	(0.622)	(1.000)	(0.153)	(0.609)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
F	31.17		67.32	33.24
r2	0.707	0.630	0.839	0.719
N	3170	3137	3144	3156

Note: Standard errors in parentheses. This table provides the reduced from coefficients of a static GDP growth evolution model. The outcome variable is the GDP growth rate (%) for a city-year. Fiscal deficit is the difference between fiscal expenditure and fiscal revenue, normalized by GDP level. I use the share of fiscal deficit out of GDP as an instrument for log land area sold. I use the average of neighbor cities' GDP growth rate as an instrument for a city's GDP growth rate. Neighbor cities are defined as those sharing borders. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.1.2 Inverse Land Demand

Next, I estimate the parameters in the inverse land demand function:

$$P_{jit} = \beta_0 + \underbrace{\beta^Q \log(Q_{jit})}_{\text{land}} + \underbrace{\beta^G G_{jit}}_{\text{GDP growth}} + \beta_i + \beta_t + \varepsilon^P_{jit}$$

To identify the demand elasticity β^Q, I need variations that shift the supply curve but are unrelated to demand shocks. Same as in Section 5.1.1, I use the share of fiscal deficit out of GDP as an instrument for land quantity. The idea is that local governments' need to raise revenues this period shifts land supply but are potentially not affected by industry's willingness to pay. Moreover, I use neighbor cities' average GDP growth rate to capture region economic shocks. The moment restrictions are:

$$\mathbb{E}[\varepsilon^P_{jit}\ \text{IV}_{jit}] = 0$$
$$\text{Instruments: IV}_{jit}\ \in \{\text{DeficitShare}_{jit},\ NG_{jit}\}$$

Table 4 reports the estimates from the reduced form and the corresponding first-stage regressions. In all specifications, I include city FEs and year FEs. Both instruments are strong, and the estimates in 2SLS have larger magnitudes than in OLS.

5.1.3 Probability of Advancing

City managers' probability of being promoted is estimated by a probit model:

$$\mathbb{P}(A_{jit} = 1) = \Phi(\alpha_{1t} + \underbrace{\alpha_{2t} \cdot \mathbb{E}[\overline{H}_{jit}]}_{\text{avg. target hitting}} + \alpha_i)$$

where the expected average probability of hitting targets for a manager j since he/she was assigned to city i until year t is:

$$\mathbb{E}[\overline{H}_{jit}] = \begin{cases} \frac{1}{2}\left(\overline{H}_{jit} + \mathbb{E}[H_{jit}]\right) & \text{if } j(i,t) = j(i,t-1) \\ \mathbb{E}[H_{jit}] & \text{if } j(i,t) \neq j(i,t-1) \end{cases}$$

I split the sample into four periods, based on presidents and congress years. The levels of advancing probability vary by president and congress year, as indicated by α_{1t}. Moreover, the importance of the history of economic performance is also allowed to be different in

Table 4: Inverse Land Demand

	(1)	(2)	(3)	(4)
	OLS	2SLS	First Stage OLS	
	Land Price	Land Price	Log Land Area Sold	GDP Growth
Log Land Area Sold	-0.455***	-3.302***		
	(0.0531)	(0.682)		
GDP Growth	0.0344***	0.132***		
	(0.0108)	(0.0339)		
Fiscal Deficit/GDP			1.832***	2.601**
			(0.301)	(1.176)
Neighbors' GDP Growth			0.0269***	0.828***
			(0.00494)	(0.0192)
Constant	6.416***	9.408***	1.100***	-0.0344
	(0.430)	(0.925)	(0.156)	(0.608)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
F	15.85		66.70	38.50
r2	0.551	0.113	0.838	0.748
N	3175	3143	3145	3161

Note: Standard errors in parentheses. This table provides the reduced form coefficients of a static inverse land demand model. The outcome variable land price is the average price of land leased in a given city-year, in terms of thousand Yuan per square meter. Fiscal deficit is the difference between fiscal expenditure and fiscal revenue., normalized by GDP level. We use the share of fiscal deficit out of GDP as an instrument for log land area sold. I use the average of neighbor cities' GDP growth rate as an instrument for a city's GDP growth rate. Neighbor cities are defined as those sharing borders. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

different periods, as captured by α_{2t}:

$$\begin{aligned}\alpha_{1t} = \alpha_{11} \cdot \mathbb{I}(\text{Hu, Non-congress}) + \alpha_{12} \cdot \mathbb{I}(\text{Hu, Congress}) +\\ \alpha_{13} \cdot \mathbb{I}(\text{Xi, Non-congress}) + \alpha_{14} \cdot \mathbb{I}(\text{Xi, Congress})\\ \alpha_{2t} = \alpha_{21} \cdot \mathbb{I}(\text{Hu, Non-congress}) + \alpha_{22} \cdot \mathbb{I}(\text{Hu, Congress}) +\\ \alpha_{23} \cdot \mathbb{I}(\text{Xi, Non-congress}) + \alpha_{24} \cdot \mathbb{I}(\text{Xi, Congress})\end{aligned}$$

Table 5 reports the estimates, controlling for city fixed effects as cities may have different political importance. Notably, managers benefit the most from better economic performance during congress years under President Hu. On the other hand, the estimates are not significant and even slightly negative in Xi's time due to shifts in evaluation criteria and anti-corruption campaigns.

Table 5: City Manager's Advancing Probability

	Estimates	Std. Error
Hu, Congress	0.655**	(0.323)
Xi, Non-Congress	0.612**	(0.264)
Xi, Congress	0.856***	(0.321)
Interaction with E[Avg. Hit]		
Hu, Non-Congress	0.306	(0.322)
Hu, Congress	1.005***	(0.343)
Xi, Non-Congress	-0.628*	(0.364)
Xi, Congress	0.434	(0.493)
Constant	-1.195**	(0.491)
City FE	Yes	
N	1738	

Note: Standard errors in parentheses. This table provides the reduced form coefficients of predicting city managers' probability of advancing. The dependent variable is a manager's actual outcome of advancing or not. The omitted group is city manager and year observations in non-congress years when Hu was the president. Expected average hit measures the expected average probability of hitting GDP growth rate targets during a manager's tenure, reset for each manager. It is an expected value as I use the expectation of the current year's GDP growth rate instead of the actual growth. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.1.4 GDP Growth Target

Tomorrow's GDP growth rate target is modeled as a function of today's GDP growth target and today's performance relative to the target. In particular, both the function's level and slope depend on whether a city hit the target in the previous year and how far away from the target. I estimate the $\nu's$ using ordinary least squares and control for the city fixed effects and year fixed effects:

$$G^*_{ji,t+1} = \nu_0 + \underbrace{\nu_{GT} G^*_{jit}}_{\text{lag target}} + \underbrace{\nu_H \mathrm{H}_{jit} + \nu_{HD} \mathrm{H}_{jit} \mathrm{Dev}_{jit} + \nu_{MD}(1 - \mathrm{H}_{jit}) \mathrm{Dev}_{jit}}_{\text{lag hit and deviation}} + \nu_i + \nu_{t+1} + \varepsilon^{G^*}_{i,t+1}$$

Table 6 reports the OLS estimates. Overall, the model predicts targets well and explains 85.9% of the variations in GDP growth targets. Also, cities that hit the target this year are associated with higher targets next year. The increase in targets correlates with the distance from targets, with the slope being steeper if the actual growth was above the target last year.

Table 6: City GDP Growth Target Setting

	(1) Estimates	(2) Std. Error
Lag City Target	0.692***	(0.0142)
Lag Hitting Target=1	0.201***	(0.0745)
Lag Hitting Target=0 × Lag Deviation	0.245***	(0.0163)
Lag Hitting Target=1 × Lag Deviation	0.273***	(0.0208)
Constant	1.300***	(0.344)
Year FE	Yes	
City FE	Yes	
F	57.38	
r2	0.859	
N	2400	

Note: Standard errors in parentheses. This table reports the OLS estimates of coefficients in the GDP growth rate target transition. The outcome variable is GDP growth rate targets. Lag hitting target equals one if previous years' actual GDP growth rate equals or is larger than the target. Lag deviation is the difference between the previous year's actual GDP growth rate and that year's target. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Second Stage

In this section, I estimate managers' relative weights on growth incentives and marginal costs for leasing land. To account for regime changes in evaluating city managers, I allow the weights to differ by presidents. Also, the marginal cost function is specified in Equation

(4.4):

$$\omega = \omega_H \mathbb{I}(\text{President Hu}) + \omega_X \mathbb{I}(\text{President Xi})$$
$$MC_{jit} = c_0 + c_1 \cdot \text{population density}_{jit} + c_2 \cdot \mathbb{I}(2009 \leq t \leq 2012)$$

Thus, the dynamic parameters to be estimated are $\theta_2 = \{\omega_H, \omega_X, c_0, c_1, c_2\}$.

To facilitate estimation, I discretize the control variable, land quantity Q_{jit}, into five bins for each city. I discretize each city's endogenous state variables into ten bins: lag GDP growth $G_{ji,t-1}$, GDP growth rate target G^*_{jit}, and the lag average probability of hitting target $\overline{H}_{jit}$.

The dynamic parameters are estimated in two steps. The inner loop takes the first stage estimates $\hat{\theta}_1$ and a guess of dynamic parameters $\tilde{\theta}_2$ as given. It performs the policy function iterations to compute the value function, and returns the optimal land quantity $\hat{Q}(S_{jit}|\tilde{\theta}_2, \hat{\theta}_1)$. To compute the static payoff within each iteration, I first calculate the chance of being promoted and the expected land profits, using the policy function from the previous iteration. Then I calculate the continuation value. Since calendar year is a state variable, for the last year in my sample, the year 2017, I assume the world is stationary in the future and computes the value function following (Pakes, Ostrovsky, and Berry, 2007). For all previous years, the problem is non-stationary. The continuation value is just the average of the value function evaluated at all future states, weighted by the probability of transitioning into each state. Moreover, since city is not treated as a state variable to avoid the curse of dimensionality, the value function is computed separately for each city. Appendix D includes a step-by-step description.

In the outer loop, I search over possible values of θ_2' to minimize the sum of the squared difference between observed quantity $Q(S_{jit})$ and the model predicted quantity $\hat{Q}(S_{jit}|\theta_2', \hat{\theta}_1)$:

$$\min_{\theta_2'} \sum_{jit} [Q(S_{jit}) - \hat{Q}(S_{jit}|\theta_2', \hat{\theta}_1)]^2$$

The θ_2' that minimizes this distance is the second stage estimate $\hat{\theta}_2$.

5.3 Second Stage Estimation Results

Table 7 reports the dynamic model estimates. The key parameters of interest are city managers' relative weights on the probability of promotion based on hitting GDP growth rates targets relative to expected land profits. This relative weight is 339 from 2003 to 2012 when Hu was the president, reflecting the central government's emphasis on developing the economy. For 2013-2017, it drops sharply to -41 due to the change of leadership.

Mechanically, as shown in Table 5, the impacts of hitting targets more often on promotion are larger and more significant during Hu's presidency. In contrast, from 2003 to 2017, better economic performance did not necessarily improve the chance of getting promoted and was even negative in certain years. This shift in evaluation metrics feeds into the dynamic estimation and partly explains the negative weights on growth incentives. Moreover, a negative estimated weight does not suggest that city managers do not care about promotion per se. The advancing function only captures the channel of advancing politically through higher GDP growth rates. After 2012, the central government changed the way of evaluating city managers and focused more on ecological benefits and social welfare. Correspondingly, local government officials may also care less about GDP growth and put more effort into other tasks. In addition, when Xi took office, large-scale campaigns were launched to crack down on corruption among both high-ranking officials and local civil servants. Since in many places, rapid growth may be accompanied by "special deals"(Bai, Hsieh, and Song, 2019), we may expect to see more city managers from high growth regions being prosecuted. Government officials not being investigated may also be more cautious in developing the local economy.

Table 7: Dynamic Model Estimates

(1) Parameter	(2) Estimates	(3) Std. Error
ω_H	339***	(77.02)
ω_X	-41**	(19.90)
c_0	0.169***	(0.05)
c_1	0.32***	(0.04)
c_2	0.0004	(0.0006)

Standard errors in parentheses are computed from 211 bootstraps, clustered at the province level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the dynamic parameter estimates from the second stage. We are interested in the weight on the probability of promotion based on hitting GDP growth rates targets relative to expected land profits. This weight was 339 from 2003 to 2012 when Hu was the president, reflecting the central government's emphasis on developing the economy. It dropped to -41 after the change of leadership in 2013. The marginal cost of leasing land is higher for cities with higher population density.

The second stage also estimates the marginal cost for leasing land, which is parameterized as a function of cities' average population. Table 8 reports that the median population density is around 32 people per square kilometers. In order to under the cost parameters, take Binzhou city in Shandong province as an example. This city has an average population density of around 39.2 people per square kilometer, close to a median density. Its marginal cost of leasing land is approximately $0.169+0.32\times0.0392$ or 182 Yuan/m^2. The average land price in the city is 484 Yuan/m^2, and it leases around 7.09 million m^2 in a year. Ignoring fixed costs, annual land profit could reach $(0.484-0.182)\times7.09=2.14$ billion Yuan or 309 million US dollars.

How large are land profits for Binzhou? The city's annual GDP level is around 155 billion Yuan, and the fiscal deficit is around 6 billion Yuan. Although land profits are pure transfers and do not count toward GDP, the inferred profits are around 1.3% of the GDP and could finance one-third of the fiscal deficit. According to Binzhou's land requisition compensation standard in 2020, the general rates range from 63 to 78 thousand Yuan per Mu, or 96 to 117 Yuan/m^2. This fee is the sum of the compensation designated for the land and the relocation of residents. Local governments also compensate for crops and structures. There may be several other costs as discussed in Section 2.3. Moreover, the estimated marginal cost is the cost *perceived* by city managers, which is probably smaller than the actual costs paid by local governments. Nevertheless, overall the estimates have the same order of magnitude as the costs published in official documents.

Table 8: Summary Statistics for Interpreting Estimated Marginal Cost

	Price	**Population Density**	**Estimated Marginal Cost**	**Markup**
Unit	000Yuan/m^2	people/hundred m^2	000Yuan/m^2	000Yuan/m^2
Mean	1.056	0.045	0.183	0.873
p25	0.426	0.017	0.174	0.246
p50	0.659	0.032	0.179	0.478
p75	1.085	0.060	0.188	0.898
N	4,302	4,302	4,302	4,302

Note: Price refers to the average lease price in a city-year. Population density is the average for a city across years. Marginal cost is estimated by the model. Markup is calculated as average price minus marginal cost.

Similar calculations can be done for other cities. Table 9 reports the mean of land profits across cities by city tier, with units in billion Yuan. To assess the importance of land profits for city governments, I compute its share out of governments' total revenues:

$$\text{Share of Total Revenue} = 100\times\frac{\text{Land Profit}}{\text{Land Profit} + \text{Tax Revenue}}$$

Land profits take a larger share in tier two cities and are on average 33.72% of governments' main revenue. Tier three and tier one cities follow, and the smallest share is in tier four cities. It reflects that the profits incentive is the strongest in the land market equilibrium in tier two cities and is in line with findings in the literature.

Table 9: Summary Statistics: Mean by City Tier

Tier	**Land Profit**	**Tax Revenue**	**Share of Total Revenue**
1	61.52	205.61	20.55
2	25.18	39.91	33.72
3	8.08	13.61	31.54
4	2.29	5.54	19.72
Total	6.78	13.72	23.58

Note: This table reports the mean of land profits and tax revenue across cities by city tier. The unit is billion Yuan. The share of total revenue is the share of land profits out of the sum of land profit and fiscal revenue. The unit is percent. This number of the highest for tier 2 cities, which suggests they have the highest profit incentives.

Is the estimated markup too high? In a static model, the land price needs to cover both marginal costs and the lost chance of advancing politically. The second component is not concerned by a pure monopolist. As in Equation (4.6), the dynamic first-order condition also includes the derivative of the continuation value with respect to land quantity. Thus, the land price has to cover the current cost and the loss of utilities in the future.

6 Counterfactuals

Armed with the dynamic estimates, I consider four counterfactuals in this section by changing the weights on political incentives. Different scenarios are summarized in Table 10. Recall the Bellman equation for a forward-looking city manager:

$$V(S_{jit}) = \max_{Q(S_{jit})} \omega \underbrace{\mathbb{P}(A_{jit}=1)}_{\text{prob. advancing}} + \underbrace{(\mathbb{E}[P_{jit}] - MC_{jit})\, Q_{jit}}_{\text{expected profit}} + \underbrace{\rho \int_s V(S_{ji,t+1})\, dF(S_{ji,t+1}|S_{jit}, Q(S_{jit}))}_{\text{continuation value}}$$

The baseline uses the weights estimated by the full dynamic model. In the no growth incentives counterfactual, I set the weight ω_H between 2003 and 2012 to zero, while keeping ω_X for 2013 to 2017 as the estimated value $\hat{\omega}_X$. In the no negative incentives world, both weights are set to zero. In the no regime shift scenario, I set ω_X equal to $\hat{\omega}_H$. Lastly, I change the discount factor from 0.95 to zero and analyze the static equilibrium.

Intuitively, as introduced in Section 4.1, there are three endogenous state variables: the lag GDP growth rate $G_{ji,t-1}$, GDP growth rate target G^*_{jit}, and the lag average probability of hitting targets $\overline{H}_{jit}$. When I shut down dynamics, GDP growth rate targets do not matter for agents' behaviors. However, the other two variables still affect the optimal land

Table 10: Counterfactual Scenarios

Parameters	Baseline	No Growth Incentives	No Negative Incentives	No Regime Shift	No Dynamics
ω_H	339	0	0	339	339
ω_X	-41	-41	0	339	-41
ρ	0.95	0.95	0.95	0.95	0

Note: ω_H is the relative weight during Hu's presidency, and ω_X is the weight during Xi's presidency. ρ is the discount factor. Baseline uses the dynamic model estimates.

supply through expected profits and the advancing function. When I shut down the political incentives channel, future targets and the probability of hitting targets drop out from the objective function because it only enters into payoffs through the advancing probabilities. However, current GDP growth affects future GDP growth, which then affects land demand; city managers still have dynamic benefits to supply more land today.

6.1 No Growth Incentives

In this section, I conduct the counterfactual analysis to estimate the impact of GDP growth incentives on land supply. I ask the question: What land quantities would city managers choose during Hu's presidency if there were no political incentives for achieving GDP growth rate targets? To get a clear picture of excess land supply driven by growth incentives, I focus on the pre-2012 period counterfactual and hold city managers' expectations of the future as constant.

To estimate the counterfactual, I set the weight on political incentives before 2012 (ω_H) to zero. Since changing ω_X would not only change the optimal decisions during Xi's time but also affect pre-2012 actions through the continuation value, I keep the weight after 2013 (ω_X) at the value estimated by the model. Finally, I re-compute each city's value function and find the optimal land quantity that maximizes the objective function.

Given the same ω_X as in the baseline model, there are two main channels through which changing ω_H from $\hat{\omega}_H = 339$ to zero affects the optimal land quantity. First, since the advancing function, which positively depends on hitting the GDP growth target, no longer enters into the objective function, there are no more benefits of having a higher GDP growth rate. Therefore, given the same market condition, city managers would decrease land supply to get higher profits. The second channel goes in the opposite direction. In the baseline, both promotion and targets are relevant. Higher GDP growth raises future targets and generates negative utility, exerting downward pressure on the optimal land supply. In contrast, targets are no longer relevant in the counterfactual. As a result, city managers would be willing to provide more land. The final direction of the counterfactual relative to the baseline depends on which force dominates.

Overall, I find that removing growth incentives results in a decrease of 0.41 million square meters of equilibrium land supply in an average city per year before 2012. To put this in perspective, the amount of land being leased in an average city-year is 5.52 million square meters, and this drop translates to 7.4% of the total land leases. When aggregated across all 213 cities used in our sample, it amounts to 873.3 million square meters (or 337.2 square miles) of extra land leased between 2003 and 2012, driven by growth incentives.

6.1.1 Distributional Impacts

To understand the distributional impacts among cities, I look at the excess land supply by city tier. Cities are usually grouped into tiers based on factors such as population and GDP level per capita. I follow the classification used by E-house, a Shanghai-based housing think-tank.[16] For example, tier one includes only four cities: Beijing, Shanghai, Guangzhou, and Shenzhen. It has the highest income level, reaching 129,402 Yuan (20,110.96 USD) per capita in 2015. In contrast, tier four cities only had an average per capita GDP of 40860 Yuan (6,350.24 USD) in 2015. Not surprisingly, housing prices are the lowest in tier four cities.

I find that growth incentives result in larger excess supply in lower-tier and smaller cities. As shown in Table 11 Panel A, moving from the baseline model prediction to the counterfactual without growth incentives, the equilibrium land supply drops more than 0.4 million square meters in a tier three or four city each year. Moreover, since tier four cities are usually smaller and lease less land in general, the impacts are much larger and account for more than 12% of all land being leased in these cities. In contrast, the drop in tier two cities is 1.27%. As reported in 11 Panel B, this extra land supply boosts the GDP growth rates by 0.2 percentage points for all cities on average. In particular, the GDP growth rates for tier four cities in the baseline are on average 0.27 percentage points higher. These findings suggest that land markets in smaller cities, especially tier four cities, are most affected by growth incentives.

Looking into the economic performance data, smaller cities also seem to have more difficulty in achieving GDP growth targets. This pattern exists during both Hu's and Xi's time. For example, Table 12 shows the average difference between each year's actual GDP growth rate and the GDP growth rate target across cities in each tier. Overall, only tier 4 cities'

[16]Thanks to the research director Yuejin Yan for sharing the data.

Table 11: Impacts of Growth Incentives by Tier

Panel A. Mean Land Supply					
	(1)	(2)	(3)	(4)	(5)
Tier	**Data**	**Baseline**	**Counterfactual**	**Change**	**%Δ**
1	9.56	8.70	8.72	-0.02	-0.21
2	12.10	10.59	10.46	0.13	1.27
3	6.77	6.52	6.08	0.44	6.79
4	3.80	3.88	3.39	0.49	12.52
Total	5.55	5.52	5.11	0.41	7.49
Panel B. Mean GDP Growth Rates					
	(1)	(2)	(3)	(4)	(5)
Tier	**Data**	**Baseline**	**Counterfactual**	**Change**	**%Δ**
1	12.33	13.13	13.15	-0.01	-0.10
2	13.92	13.82	13.79	0.03	0.18
3	13.83	13.93	13.79	0.14	1.02
4	13.69	13.86	13.59	0.27	1.96
Total	13.72	13.85	13.65	0.20	1.45

Note: Panel A compares the mean of equilibrium land supply in the baseline model and the counterfactual with no growth incentives. The units for columns (1) to (4) are million square meters. Panel B compares the mean of GDP growth rates in the baseline model and in the counterfactual with no growth incentives. The units for columns (1) to (4) are percent.

average GDP growth rates are 0.44 percentage points below their targets, while all other cities hit the targets on average. However, when economic performance was more important for advancing (2003-2012), cities from all tiers on average did achieve GDP growth rates higher than the targets *ex-post*. Figure 5 plots the time series of these deviations, where all tiers have actual growth closer or above targets before 2012 and is consistent with the hypothesis that tier 4 cities used land supply as tools to stimulate the economy.

Table 12: Actual GDP Growth Rate Minus Target

Tier	Full Sample	2003-2012	2013-2017
1	1.29	2.06	0.13
2	0.41	1.38	-0.71
3	0.37	1.33	-0.74
4	-0.44	0.66	-1.62
Total	-0.13	0.94	-1.31

Note: This table reports the mean difference between cities' actual GDP growth rates and growth rate targets. The units are percent.

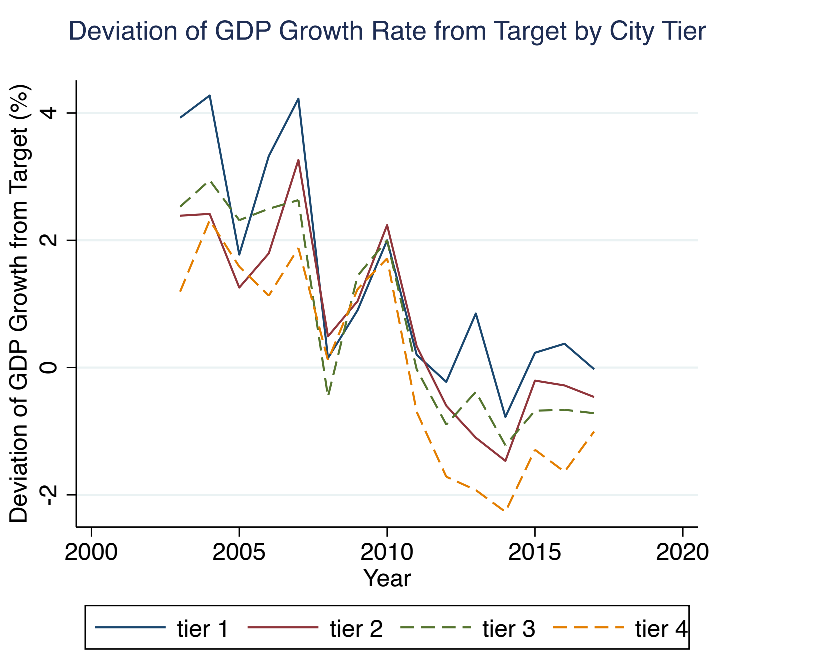

Figure 5: A comparison of the actual GDP growth rate relative to the GDP growth targets by city tier. Notably, tier four cities have ex-post the lowest performance for given targets.

6.1.2 Impacts on Residential Construction

To assess the impacts of growth incentives on construction, I use a simple accounting method to bound the effects. Note that land supply data used in the estimation is the aggregate area of land from all industries. In order to translate land area into the floor space of commercial residential buildings, two statistics are needed: one is the share of residential land of total land supply. Among land sold for all industries, commercial residential land takes about 25%. The other one is the floor area ratio, which is the ratio of a building's total floor area to the size of the land parcel upon which it is built. The common range goes from below 1 for independent houses to 5 for high-rise apartments for residential housing. I compute a lower bound using 25% housing land share and a floor-area ratio of 3, and an upper bound with 30% housing land share and a floor area ratio of 3. On average, the extra construction due to growth incentives ranges from 0.31 to 0.37 million square meters. Aggregate across all cities for ten years, it adds up to 660.3 to 788.1 million square meters.

To put this in perspective, Rogoff and Yang (2020) computed housing oversupply as the difference between cumulative residential floor space started minus cumulative residential floor space sold. The cumulative gap by the end of 2018 is estimated at 2,850 million square meters. Taking the extra construction estimates, the lower bound could explain 23.2%, and the upper bound could explain 27.7% of this housing over-supply.

6.2 No Negative Incentives

This section estimates the counterfactual land supply by removing political incentives in both Hu's and Xi's presidency. To do this, I set the weights on the advancing function in both periods to zero: $\omega_H = \omega_X = 0$. The results are reported in Panel A of Table 13. Similar to the previous section, changing ω_H from $\hat{\omega}_H = 339$ to zero leads to lower land supply from 2003 to 2012. However, the magnitude in the drop is slightly smaller: 6.9% as opposed to 7.49% in section 6.1.

Theoretically, in this counterfactual, the continuation value is higher. By switching off ω_X, it eliminates the negative impacts of having a higher GDP growth and the positive impacts of higher targets. Since the former force dominates, a pure dynamic monopolist has a higher utility from providing extra land and would sell more than city managers influenced by political incentives. However, it is still a dynamic problem as GDP growth today affects future economic conditions that enter into the land demand function. Specifically, after 2013, city managers would supply 1.04 million more lands for an average city-year without considering political outcomes. This land oversupply translates to 12.6% of all land being leased.

Table 13: Mean of Additional Counterfactual Land Supply

Panel A. No Negative Incentives					
Time Period	**Data**	**Baseline**	**Counterfactual**	**Change**	**%Δ**
2003-2012	5.55	5.52	5.14	-0.38	-6.90
2013-2017	8.41	8.28	9.32	1.04	12.60
Panel B. No Regime Shift					
Time Period	**Data**	**Baseline**	**Counterfactual**	**Change**	**%Δ**
2003-2012	5.55	5.52	5.59	0.07	1.26
2013-2017	8.41	8.28	12.06	3.78	45.61
Panel C. No Dynamics					
Time Period	**Data**	**Baseline**	**Counterfactual**	**Change**	**%Δ**
2003-2012	5.55	5.52	5.46	-0.07	-1.23
2013-2017	8.41	8.28	6.00	-2.28	-27.48

Note: This table reports the mean land supply in additional counterfactuals. Panel A sets both weights ω_H and ω_X to zero. Panel B sets ω_X to $\hat{\omega}_H$. Panel C sets the discount factor to zero.

6.3 No Regime Shift

In this section, I ask the question: what would the land market equilibrium be after 2012 if president Hu kept in power, or if president Xi maintained the GDP growth target as a key metric to evaluate local officials? To quantify this counterfactual, I hold ω_H at $\hat{\omega}_H$ and replace the weight in Xi's time ω_X with pre-2012 value $\hat{\omega}_H$. So city managers care about achieving GDP growth targets in the same way in all years. Since ω_X is raised from -41 to 339, city managers would supply more land, given that market conditions are held the same as in the baseline. Indeed, as shown in Panel B of Table 13, land supply in a average city-year increases by 3.78 or 45.61% compared with the baseline.

Furthermore, since city managers are forward-looking, the effects feed into pre-2012 decisions. When the chance of advancing in the future also positively depends on the history of economic performance, city managers respond by boosting the local economy early on. Although the magnitudes are much smaller than the pos-2012 impacts, I still find a 1.26% increase in land supply. When aggregated across 213 cities in the sample and ten years, it amounts to 149 million square meters, just driven by the belief that today's growth might matter for future evaluation.

6.4 No Dynamics

In this section, I study the importance of considering the future in modeling city managers' behaviors. Specifically, I ask: How city managers would act if they only cared about the current period. To answer this question, I set the discount factor ρ to zero, while it is calibrated to 0.95 in the baseline model. As specified in Equation (4.5), the static optimization problem is choosing the amount of land supply to maximize the weighted sum of advancing probability and expected land profits:

$$\max_{Q(S_{jit})} \pi(Q(S_{jit}), S_{jit}) = \max_{Q(S_{jit})} \omega \underbrace{\mathbb{P}(A_{jit} = 1)}_{\text{prob. advancing}} + \underbrace{(\mathbb{E}[P_{jit}] - MC_{jit})\ Q_{jit}}_{\text{expected profit}}$$

The optimal land supply computed by this counterfactual may differ from the full model's prediction in three main ways: future GDP growth targets, future land profits, and future advancing probability. First, during 2003-2012, city managers no longer bear in mind that better performance today would leave future selves with higher GDP growth targets and thus more challenging tasks. Since the future target concern dampens the benefits of boosting today's GDP growth, removing this concern would encourage city managers to lease more land. Second, in the baseline model, achieving today's GDP growth rate counts as performance history for tomorrow, so a higher growth today contributes to a higher chance of advancing in the future. When city managers put zero weight on future selves, hitting today's GDP growth targets only improves the current period's chance of advancing. Hence the benefits of expanding economic output today are reduced, and they may supply less land. Lastly, expected future land profits positively depend on future economic growth, which increases with today's GDP growth. Thus, future profits add another reason for supplying more land. When it is ignored, city managers would have less incentive to provide land.

Panel C in Table 13 presents the results. In both periods, setting the discount factor to zero results in lower land supply and suggests that profits and advancing forces dominate the target channel. However, the magnitude is much larger after 2012. While city managers reduce land supply by 1.23% pre-2012, the drop is 27.48% afterward. Mechanically, land cost is a function of a city's average population across years, fixed over time. However, average land prices have risen from 790 Yuan/m^2 (or 11.39 USD/ft^2) between 2003 and 2007 to 1,509 Yuan/m^2 (or 21.76 USD/ft^2) between 2013 and 2017. Thus, the marginal revenue of leasing a land parcel is much higher in later periods. Since our model is non-stationary, the continuation value would also be higher for city managers after 2012, and the impacts would be larger if dynamics were ignored.

7 Conclusion

How do local bureaucrats' political incentives explain the vast number of unsold and unoccupied homes in China? This paper starts with two facts. First, city managers are promoted based on local economic performance. Second, local governments are monopolists in selling land leaseholds, which is crucial for economic activities. Thus, city managers have not only the incentives but also the tools to boost the local economy.

I build and estimate a structural model in which forward-looking city managers choose the amount of land to lease. Their objective is to maximize the weighted sum of the probability of being promoted and the expected land profits. This model highlights the trade-offs in city managers' decision-making. On the one hand, they want to make more land available to stimulate the economy. On the other hand, in order to fund government expenditures, they want to maximize land profits by restricting land supply.

I find that city managers sell 7.4% more land between 2003 and 2012, compared to a counterfactual where city managers have no GDP growth incentives. The magnitude is larger in smaller cities, which reaches 12.52%. These cities rely more on the government to achieve higher growth rates. Finally, after converting extra land supply to construction, the estimated impacts of growth incentives explain 23.2% to 27.7% of the excess housing construction. Thus, this paper characterizes a source of construction booms and provides a framework for quantifying the role of political incentives in market outcomes.

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Appendices

A Figures

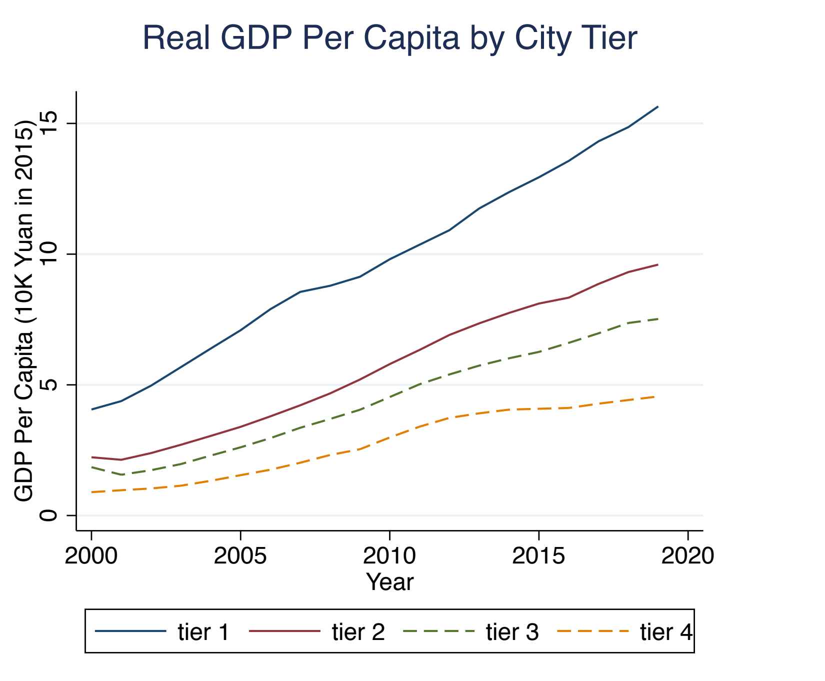

Figure A1

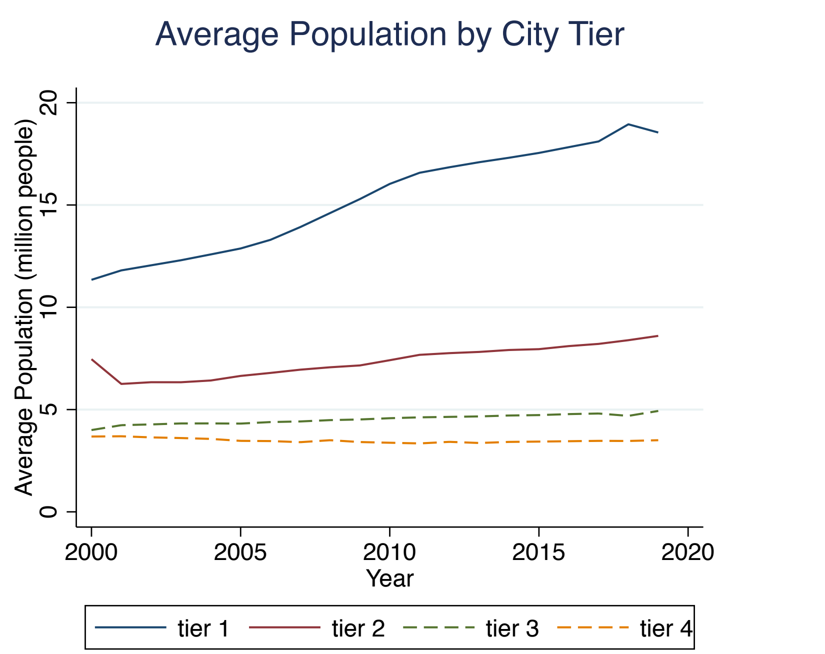

Figure A2

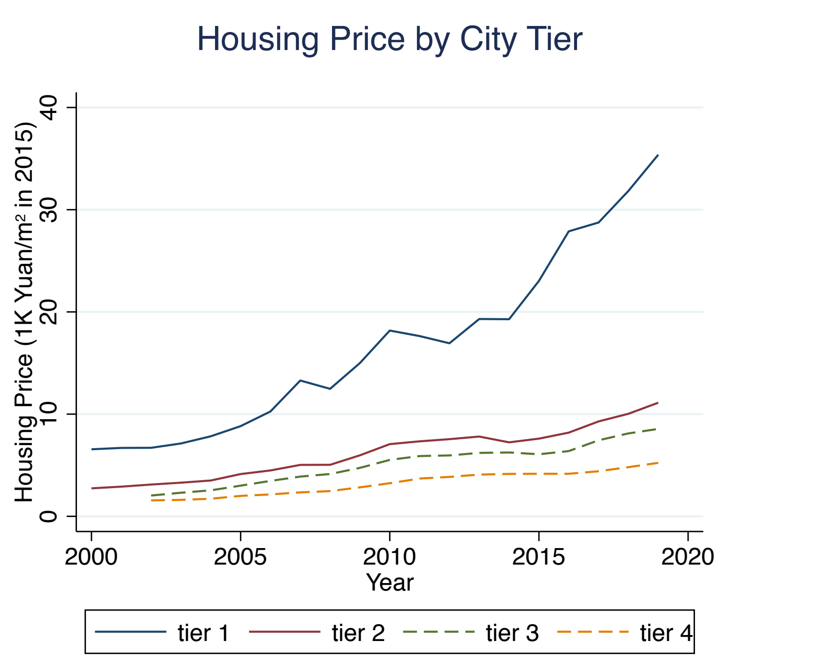

Figure A3

B Tables

Table B1: City Managers' Resume End Month

Move after 2001				Move during 2008				Move during 2013			
Month	Freq.	Percent	Cum.	Month	Freq.	Percent	Cum.	Month	Freq.	Percent	Cum.
1	248	16.51	16.51	1	53	41.73	41.73	1	25	21.01	21.01
2	181	12.05	28.56	2	31	24.41	66.14	2	28	23.53	44.54
3	151	10.05	38.62	3	13	10.24	76.38	3	16	13.45	57.98
4	126	8.39	47	4	8	6.3	82.68	4	12	10.08	68.07
5	108	7.19	54.19	5	3	2.36	85.04	5	5	4.2	72.27
6	85	5.66	59.85	6	3	2.36	87.4	6	4	3.36	75.63
7	88	5.86	65.71	7	3	2.36	89.76	7	6	5.04	80.67
8	98	6.52	72.24	8	3	2.36	92.13	8	4	3.36	84.03
9	91	6.06	78.3	9	3	2.36	94.49	9	5	4.2	88.24
10	60	3.99	82.29	10	1	0.79	95.28	10	3	2.52	90.76
11	97	6.46	88.75	11	3	2.36	97.64	11	4	3.36	94.12
12	169	11.25	100	12	3	2.36	100	12	7	5.88	100
Total	1502	100		Total	127	100		Total	119	100	

Note: This table reports the frequency of city managers being moved by month. Party secretaries usually leave the office at the end of the year or early next year. Among those who moved after 2001, around 50% left the office in December or by the end of March. The proportion was even higher in the year right after the party congresses.

Table B2: Tabulation of City Manager Tenure (year)

Full Sample (2003-2017)				**President Hu (2003-2012)**				**President Xi (2013-2017)**			
Tenure	Freq.	Percent	Cum.	Tenure	Freq.	Percent	Cum.	Tenure	Freq.	Percent	Cum.
1	146	10.49	10.49	1	69	7.58	7.58	1	77	15.98	15.98
2	249	17.89	28.38	2	127	13.96	21.54	2	122	25.31	41.29
3	270	19.4	47.77	3	189	20.77	42.31	3	81	16.8	58.09
4	334	23.99	71.77	4	203	22.31	64.62	4	131	27.18	85.27
5	201	14.44	86.21	5	156	17.14	81.76	5	45	9.34	94.61
6	102	7.33	93.53	6	88	9.67	91.43	6	14	2.9	97.51
7	46	3.3	96.84	7	42	4.62	96.04	7	4	0.83	98.34
8	27	1.94	98.78	8	19	2.09	98.13	8	8	1.66	100
9	12	0.86	99.64	9	12	1.32	99.45				
10	4	0.29	99.93	10	4	0.44	99.89				
11	1	0.07	100	11	1	0.11	100				
Total	1,392	100		Total	910	100		Total	482	100	

Note: This table provides a detailed frequency tabulation of city managers' tenure. Overall, more than 86% of city managers left the office during the first term.

C GDP Calculation

There are three equivalent ways to calculate GDP that reflect the economy's production from different angles: the production, income, and expenditure approaches.[17] (1) The production approach computes value-added by subtracting the value of intermediate goods and services from the value of goods and services created in the production process. That is: value-added = total output - intermediate inputs. The GDP by production approach is the sum of value-added by production approach of various industries of the national economy. (2) The income approach measures the production activities from the point of generating income during the production process. The accounting formula is: value-added = workers compensation + net taxes on production + depreciation of fixed assets + operating surplus. (3) The GDP by income approach equals the sum of value-added by income approach of various industries of the national economy. The GDP by expenditure approach calculates GDP from the perspective of the final uses of production activities, including final consumption expenditure, gross capital formation, and net export of goods and services.

Regarding production range, GDP accounting includes the following four parts: first, the production of goods and services provided to or ready to provide to other units by the producers; second, self-sufficient production of goods for own final consumption or capital formation by the producers; third, self-sufficient production of knowledge carrier products for own final consumption or capital formation by the producers, excluding similar activities undertaken by the household sector; fourth, housing services provided by owner-occupied housing, as well as self-sufficient production of household and personal services provided by paid family service personnel. Production range does not include unpaid household and personal services, nor no units controlled natural activities (such as wild, non-cultivated forest, berries or wild berries natural growth, the natural growth of the number of fish in the public sea), etc.

D Estimating Value Function

For each city and for a given guess of θ_2, I run the following policy function iterations. Initial conditions are $Q_{old} = Q_0$ and $V_{old} = V_0$:

1. Given Q_{old}, compute static payoff Π
2. Given Q_{old}, compute transition matrix F

[17]Source: http://www.stats.gov.cn/english/PressRelease/202012/t20201231_1811928.html

- If $t \geq T$, set $\nu_{t+1} = \nu_T$

3. Given Π, F, and V_{old},
   - If $t < T$, compute value function $V_{new} = \Pi + \rho F V_{old}$
   - If $t \geq T$, assume stationarity $V = \Pi + \rho F V$ and compute $V_{new} = (I - \rho F)^{-1}\Pi$
4. Given V_{new}, for each possible values of Q, compute $u(Q) = \Pi(Q) + \rho F(Q) V_{new}$. Update $Q_{new} = \arg\max_Q u(Q)$
5. Given Q_{old} and Q_{new}, compute criterion for convergence
6. If criterion exceeds tolerance, update $Q_{old} = Q_{new}$, advance counter, and return to 1. Else, end.

Call the final Q_{new} the predicted quantity $\hat{Q}$.

E A Stylized Model

This section presents a theoretical framework of local land and housing markets. It highlights three sources of externalities that lead to vacancies higher than the socially optimal level. In particular, the model allows land supply and housing construction to respond to city governments' political incentives endogenously. Further, the three-stage setup captures both the intensive margin of land sales and the extensive margin of construction holding land fixed.

I first use general functions to describe how land transactions, housing construction, and vacancies are determined in equilibrium. Then I run simulations to illustrate the roots of social problems.

The timing works as follows. In stage 1, the local government acquires land from farmers at some cost. Then in stage 2, it sells the land to developers, specifying the land fee and total construction on the land. Finally, in stage 3, developers build according to the contract and choose housing supply, leaving the rest of the construction vacant. The model is solved by backward induction.

E.1 Housing Market: stage 3

Developers in a city produce homogeneous housing. They construct total height T on the marginal land as specified on the land lease and choose the height to supply on the housing market h to maximize profits:

$$\max_h \Pi = P(h, \bar{h}L)h - F - K(T) \tag{E.1}$$

Housing supply on other lands $\bar{h}L$ is taken as given, where $\bar{h}$ is the average height of existing housing and L is the land stock. Therefore, the total housing supply is $h + \bar{h}L$. Residents do not move across cities but have a downward sloping demand for space within the city, so $P'(h, \bar{h}L) < 0$. The developer pays a fixed land fee F to the local government. The construction cost function is convex. That is, it costs more to build higher - $K'(\cdot) > 0$ and $K''(\cdot) > 0$. Since total construction T is set by the government, developers treat construction cost $K(T)$ as given.

Take first-order condition with respect to h, the profit-maximizing housing supply is determined by:

$$P'(h, \bar{h}L)h + P(h, \bar{h}L) = 0$$

Since developers make the same decision in equilibrium, imposing $\bar{h} = h$ gives the equilibrium housing supply:

$$P'(h, L)h + P(h, L) = 0 \tag{E.2}$$

That is, developers will sell housing up to the point where marginal cost equals zero, as the total cost $F + K(T)$ is exogenous. Developer profit is:

$$\Pi = P(h, L)h - F - K(T) \tag{E.3}$$

E.2 Land Market: stage 2

The local government's utility from selling each land has two components. One is the direct land fee; the other is the construction value that developers build on the top of the land. Since the local government is a monopoly land seller, it has all the bargaining power and sets the land fee F to extract all developer profit. From Equation (E.3), $\Pi = 0$ gives the land fee:

$$F = P(h, L)h - K(T)$$

Besides setting land fees, the local government can also choose the total construction T

that the winner developer has to build, which is the sum of housing supply h and vacancy v. Since the local government correctly anticipates the developer's decision in stage 3, choosing T is the same as choosing v. Plugging in the optimal land fee F and substituting T with $h+v$, local government's problem becomes:

$$\max_{F,T} U = F + mP(h,L)T$$
$$\max_{v} U = P(h,L)h - K(h+v) + mP(h,L)(h+v)$$

Taking the first-order condition, the optimal vacancy rate is:

$$\frac{\partial U}{\partial v} = -K'(h^*+v) + mP(h^*,L)mP(h^*,L) = K'(h^*+v^*)$$

Because it is more expensive to build higher, the construction cost function $K(T)$ is convex. Therefore, we have $v^* > 0$ as long as $mP(h^*,L) > K'(h^*)$.
As a result, local government's utility when they make the optimal choices are (stars are omitted):

$$\begin{aligned} U(L) &= Ph - K(h+v) + mP(h+v) \\ &= Ph - K(T) + mPT \\ U'(L) &= P'(L)h + Ph'(L) - K'(T)T'(L) + mPT'(L) + mP'(L)T \end{aligned}$$

E.3 Land Market: stage 1

Finally, given utility from each land, the local government chooses the amount of land to acquire and sell to maximize the total utility from all lands. The local government gains utility $U(L)$ from each of the L land, but they pay a total cost of $C(L)$ to farmers to acquire the land.

$$\max_{L} W(L) = L \cdot U(L) - C(L)$$

Taking the derivative with respect to the amount of land L, the government acquires an additional land if the marginal utility equals marginal cost:

$$U(L) + LU'(L) = C'(L)$$
$$Ph - K(T) + mPT + L \cdot [P'(L)h + Ph'(L) - K'(T)T'(L) + mPT'(L) + mP'(L)T] = C'(L)$$

Rearrange:

$$\underbrace{P\cdot[h+h'(L)L]+P'(L)hL}_{\text{housing sales}}+\underbrace{mP[T+T'(L)L]+mP'(L)TL}_{\text{GDP}}=\underbrace{C('L)}_{\text{land cost}}+\underbrace{K(T)+K'(T)T'(L)L}_{\text{construction cost}}$$

This expression gives equilibrium L^*. Intuitively, revenues and GDP utility from the marginal land have to cover the land and construction costs.

E.4 Equilibrium

In summary, the timing follows:

- Stage 1
  - Government decides total land L to acquire

$$\max_L W = L\cdot U(L) - C(L)$$

- Stage 2
  - Given L, government specifies {fee per land, total construction} $= \{F, T\}$

$$\max_{F,T} U = F + mP(h, L)T$$

  where $F = P(h, L)h - K(T)$ and $T = h + v$

- Stage 3
  - Given $\{L, F, T\}$, developer chooses housing h to sell

$$\max_h \Pi = P(h, \bar{h}L)h - F - K(T)$$

  in equilibrium, $\bar{h} = h$

The equilibrium land stock, land fee, housing, and vacancies L^*, F^*, h^*, v^* are determined by:

$P'(h,L)h + P(h,L) = 0$	monopoly developer
$F = P(h,L)h - K(T)$	zero profit developer
$mP(h^*, L) = K'(h^* + v^*)$	utility maximizing government
$U(L) + LU'(L) = C'(L)$	utility maximizing government

E.5 Comparative Statics

We hypothesize that housing vacancies would be higher if the local government has a higher weight on GDP: $\frac{\partial v}{\partial m} > 0$. However, it is not entirely straightforward as it is costly for developers to hold vacancies. Therefore, requiring the developer who wins the bid to construct more vacant buildings reduces the developer's profit and, consequently, the land fee. Since the local government also cares about land fees, there is a trade-off between utility from more construction and more land revenues.

From local government's optimal total construction decision:

$$\begin{aligned}
mP &= K'(T) \\
mP(h, L) &= K'(h + v) \\
v &= K'^{-1}(mP(h, L)) - h \\
&= K'^{-1}(Y) - h \\
\frac{\partial v}{\partial m} &= \frac{\partial K'^{-1}(Y)}{\partial m} \\
&= \frac{\partial K'^{-1}(Y)}{\partial Y} \frac{\partial Y}{\partial m} \\
&= \frac{\partial K'^{-1}(Y)}{\partial m} \cdot [P(h, L) + m\frac{\partial P(h, L)}{\partial m}] \\
&= \frac{\partial K'^{-1}(Y)}{\partial m} \cdot [P(h, L) + m\frac{\partial P(h, L)}{\partial L}\frac{\partial L}{\partial m}]
\end{aligned}$$

It is hard to sign this general functional form. Therefore, in the next section, I will simulate the comparative statics using specific functional forms.

E.6 Simulations

E.6.1 Functional Forms

I assume a linear demand for space, a convex construction cost function, and a linear land acquisition cost function:

$$\begin{aligned}
P(h, \bar{h}L) &= a - b(h + \bar{h}L) \\
K(h + v) &= k(h + v)^2 \\
C(L) &= cL
\end{aligned}$$

The equilibrium housing supply, vacant space, and land fees are:

$$h^* = \frac{a}{b(2+L)}$$
$$v^* = \left(\frac{m}{2k} - \frac{1}{b}\right)\frac{a}{2+L}$$
$$F^* = \left(\frac{1}{b} - \frac{m^2}{4k}\right)\left(\frac{a}{2+L}\right)^2$$

E.6.2 Political Incentives

We set $a = 200, b = 10, c = 5, k = 3$, and change m from 0.5 to 1.1. We first check that the downward sloping demand curve holds in both the housing and land markets. Figures E4 and E5 show that, as the political weight m on GDP gets higher, the local government sells more land and asks developers to build more housing. However, the price for each housing unit has to decrease, and so does the price for each land.

We then examine the impacts of higher political incentives on vacancy. Figure E6 plots the weight m on GDP on the horizontal axis. The vertical axis on the left-hand side shows the fraction of vacant space v in total construction $T = h + v$. The right axis shows total housing sold h^*L. We notice two things. First, as the local government cares more about GDP, that is, as m gets larger, we see a higher vacancy rate. At the same time, we have more housing h^L, which is sold in the equilibrium. Second, political incentive m has to be high enough for a local government willing to build vacant housing. In this particular example, vacancy rate is zero for $m < 0.5$.

E.6.3 Cross Partials

We keep $a = 200, c = 5, k = 3$ and change the (negative) slope of the demand curve b from 5 to 15. Figure E7 plots total vacancy against the slope b for high and low political incentives. Overall, high incentive local leaders with $m = 1$ build more vacant space than low incentive local leaders with $m = 0.7$. Also, as the slope of housing demand becomes steeper, the distance between the two curves is even larger. Moreover, the threshold for having positive vacancy is different between low and high incentive leaders.

E.7 Derivation Details

Below are more detailed calculations using specific functional forms:

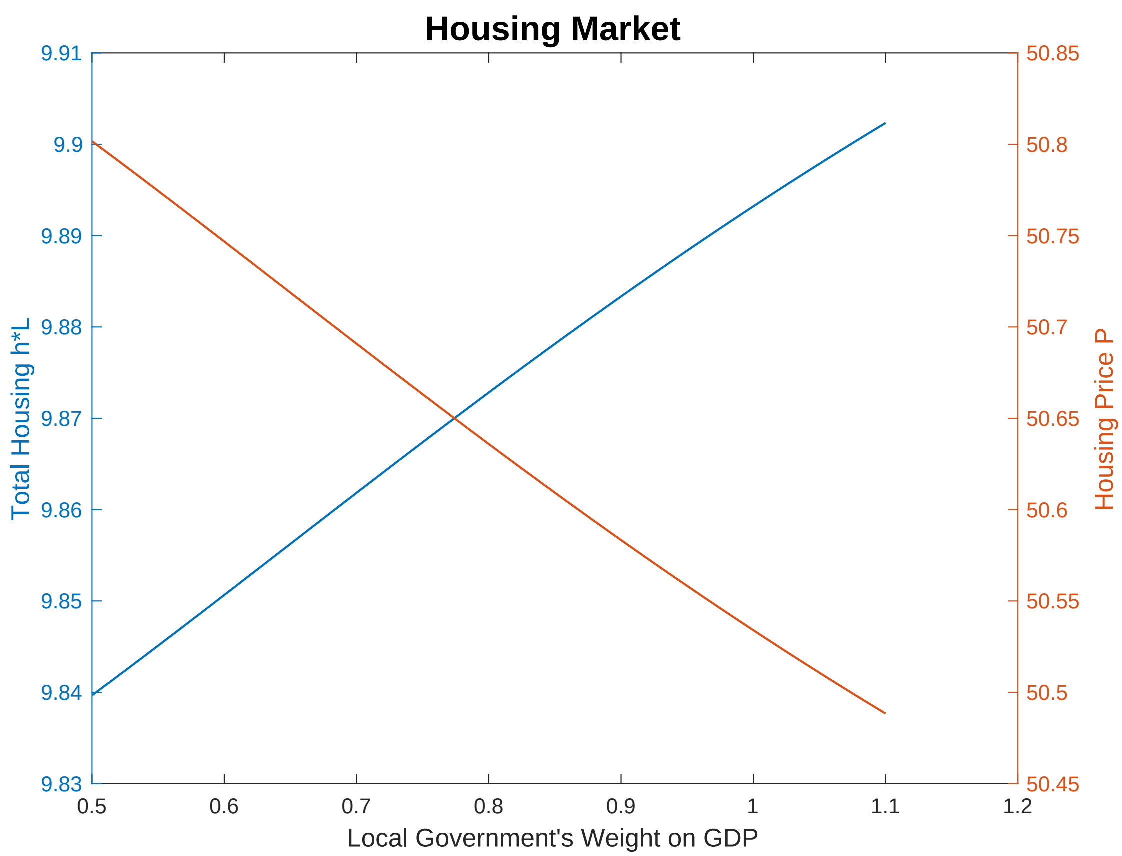
Housing Market
9.91
9.9
9.89
9.88
9.87
9.86
9.85
9.84
9.83
Total Housing h*L
50.85
50.8
50.75
50.7
50.65
50.6
50.55
50.5
50.45
Housing Price P
0.5
0.6
0.7
0.8
0.9
1
1.1
1.2
Local Government's Weight on GDP

Figure E4

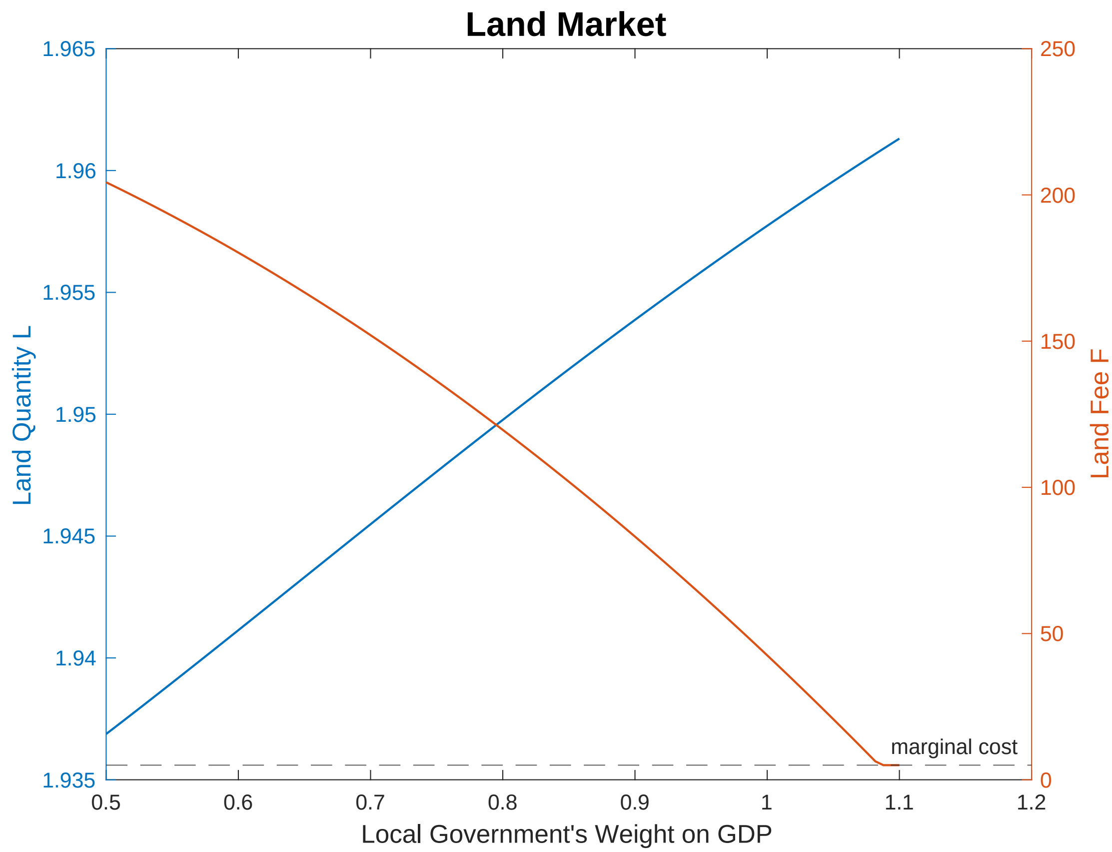
Land Market
1.965
1.96
1.955
1.95
1.945
1.94
1.935
Land Quantity L
250
200
150
100
50
0
Land Fee F
marginal cost
0.5
0.6
0.7
0.8
0.9
1
1.1
1.2
Local Government's Weight on GDP

Figure E5

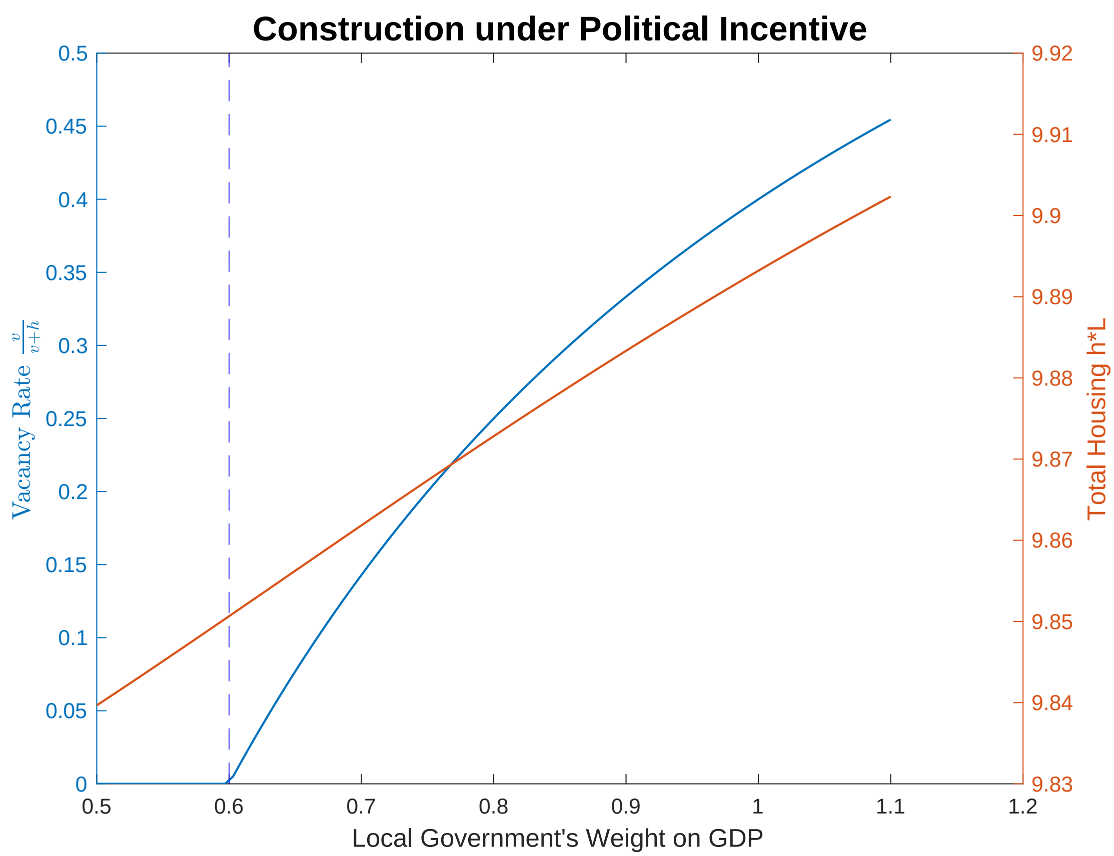
Construction under Political Incentive
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Vacancy Rate $\frac{v}{v+h}$
9.92
9.91
9.9
9.89
9.88
9.87
9.86
9.85
9.84
9.83
Total Housing h*L
0.5
0.6
0.7
0.8
0.9
1
1.1
1.2
Local Government's Weight on GDP

Figure E6


Total Vacancies Response
high vs. low incentives
high incentive (m=1)
low incentive (m=0.7)
Total Vacancies (V*L)
Negative Demand Curve Slope (b)
0
1
2
3
4
5
6
7
8
9
10
5
6
7
8
9
10
11
12
13
14
15

Figure E7

- Linear demand

$$P(h, \bar{h}L) = a - b(h + \bar{h}L)$$

- Convex construction cost function

$$K(h + v) = k(h + v)^2$$

- Linear land acquisition cost

$$C(L) = cL$$

In stage 3, developer's problem is:

$$\begin{aligned}\max_h \Pi &= P(h, \bar{h}L) - F - K(T) \\ &= [a - b(h + \bar{h}L)]h - F - K(T)\end{aligned}$$

Set the first order condition to zero:

$$\begin{aligned}\frac{\partial \Pi}{\partial h} &= 0 \\ a - b(h + \bar{h}L) - bh &= 0\end{aligned}$$

Also, $\bar{h} = h$ in equilibrium. Therefore,

$$h^*(L) = \frac{a}{b(2 + L)}$$

Plug the optimal housing into the demand function, we get housing price as a function of land:

$$\begin{aligned}P(L) &= a - b(h^* + h^*L) \\ &= \frac{a}{2 + L}\end{aligned}$$

Similarly, land fee is

$$F(v, L) = P(L)h^* - k(h^* + v)^2$$

Anticipating developers' behavior, in stage 2, the government specifies total construction $T = h^* + v$ and land fee to extract all profits:

$$\max_T U = F + mPT$$

which is equivalent to

$$\max_v U = F + mP(h^* + v)$$

First order condition:

$$\begin{aligned}
mP &= K'(h^* + v) \\
&= 2k(h^* + v) \\
h^* + v &= \frac{m}{2k}P \\
&= \frac{m}{2k}[a - bh^*(1 + L)] \\
v^* &= \left(\frac{m}{2k} - \frac{1}{b}\right)\frac{a}{2 + L}
\end{aligned}$$

Therefore, land fee becomes

$$\begin{aligned}
F(L) &= P(L)h^* - k(h^* + v)^2 \\
&= \frac{a}{2 + L}\frac{a}{b(2 + L)} - k\left(\frac{m}{2k}P\right)^2 \\
&= \frac{a}{2 + L}\frac{a}{b(2 + L)} - k\left(\frac{m}{2k}\frac{a}{2 + L}\right)^2 \\
&= \left(\frac{1}{b} - \frac{m^2}{4k}\right)\left(\frac{a}{2 + L}\right)^2
\end{aligned}$$

Finally, in stage 1, everything is a function of land quantity L. The government chooses the amount of land to buy from farmers in order to maximize utility from all land:

$$\max_L W(L) = L \cdot U(L) - C(L)$$

The first-order condition says that the government will acquire an additional land if the marginal utility equals marginal cost:

$$\begin{aligned}
U(L) + LU'(L) &= C'(L) \\
Ph - K(T) + mPT + L \cdot [P'(L)h + Ph'(L) - K'(T)T'(L) + mPT'(L) + mP'(L)T] &= C'(L) \\
P \cdot [h + h'(L)L] + P'(L)hL + mP[T + T'(L)L] + mP'(L)TL &= C'(L) + K(T) + K'(T)T'(L)L
\end{aligned}$$

Plug in functional forms, the right hand side equals:

$$\begin{aligned}
&\frac{a}{2+L}\left[\frac{a}{b(2+L)} - \frac{aL}{b(2+L)^2}\right] - \frac{a}{(2+L)^2}\frac{aL}{b(2+L)} \\
&+ m\frac{a}{2+L}\left[\frac{m}{2k}\frac{a}{2+L} + \frac{m}{2k}\frac{-a}{(2+L)^2}L\right] - m\frac{a}{(2+L)^2}\frac{m}{2k}\frac{a}{2+L}L \\
=&\frac{1}{b}\left(\frac{a}{2+L}\right)^2 - \frac{2}{b}\frac{a^2L}{(2+L)^3} + \frac{m^2}{2k}\left(\frac{a}{2+L}\right)^2 - \frac{m^2}{k}\frac{a^2L}{(2+L)^3}
\end{aligned}$$

left hand side is:

$$\begin{aligned}
&c + k(\frac{m}{2k}P)^2 + 2k(h+v)\frac{m}{2k}P'(L)L \\
=&c + k\left(\frac{m}{2k}\frac{a}{2+L}\right)^2 - 2k\frac{m}{2k}\frac{a}{2+L}\frac{m}{2k}\frac{a}{(2+L)^2}L \\
=&c + \frac{m}{4k}\left(\frac{a}{2+L}\right)^2 - \frac{m^2}{2k}\frac{a^2L}{(2+L)^3}
\end{aligned}$$

Put together and rearrange:

$$\begin{aligned}
\frac{1}{b}\left(\frac{a}{2+L}\right)^2 - \frac{2}{b}\frac{a^2L}{(2+L)^3} + \frac{m^2}{2k}\left(\frac{a}{2+L}\right)^2 - \frac{m^2}{k}\frac{a^2L}{(2+L)^3} &= c + \frac{m}{4k}\left(\frac{a}{2+L}\right)^2 - \frac{m^2}{2k}\frac{a^2L}{(2+L)^3} \\
\left(\frac{1}{b} + \frac{m^2}{4k}\right)\left(\frac{a}{2+L}\right)^2 - 2\left(\frac{1}{b} + \frac{m^2}{4k}\right)\frac{a^2L}{(2+L)^3} &= c
\end{aligned}$$

Let $X = \frac{1}{b} + \frac{m^2}{4k}$, the previous equation becomes:

$$\begin{aligned}
a^2X(2-L) &= c(2+L)^3 \\
cL^3 + 6cL^2 + (12c + a^2X)L + (8c - 2a^2X) &= 0
\end{aligned}$$

which is a cubic equation in L and its real root determines the equilibrium land quantity L^*.