Local Government Financial Constraint and Spending Multiplier in China*

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Abstract

I estimate the local government spending multiplier to be 14 at the prefecture city level in China during 2001-2019. To overcome identification challenges, I construct a novel instrument for local government spending using the fraction of unoccupied raw land in the downtown area in 2000. After the land market was formalized in 2000, a higher fraction of unoccupied raw land implies higher net profits from land sales for local governments. The fraction is uncorrelated with either the level or the growth of economic activities and infrastructure before 2000, or net land supply after 2000. The multiplier is larger for cities with higher GDP per capita and GDP growth rate before 2000, and does not depend on the benefit from WTO entry or the initial level of infrastructure. There are large positive spillovers within but not across cities. The large spending multiplier can be explained by the facts that local government spending has been productive. The increase of local government spending increases labor demand and wages, firm entry and local firms' productivity and output, especially for industries with more use of transportation services. It also generates positive spillovers through technology and supply chains.

Keywords: Local government spending multiplier, financial constraint, spillover, China.

JEL classifications: E62, G30, H32, H70.

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1 Introduction

The magnitude of the government spending multiplier, i.e., the dollar amount increase of output per dollar increase of government spending, depends on various economic factors, one of which is whether the government spending is consumption or investment. Government investment usually leads to higher multiplier than government consumption at least in the long run (Aschauer, 1989; Ramey et al., 2020). Figure 1 shows the share of local government infrastructure investment as a percentage of total spending for China during 1998-2019 and US during 1991-2019. Local governments in China constantly spend a higher fraction of their revenues in infrastructure investment than the counterparties in the US. To the extent that the local government spending in China loads more on investment and the higher share of investment spending may be due to higher marginal productivity of public capital, the overall multiplier of the general government spending in China may be quite different from that in US. In this paper, I estimate the local government spending multiplier in China during 2001-2019, and show the large multiplier found can be rationalized with productive government spending.

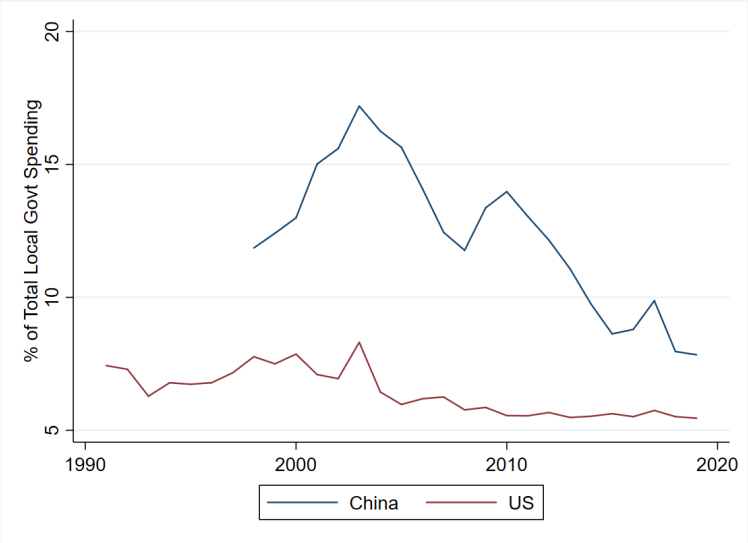


Figure 1: Government Infrastructure Investment/Total Spending: China versus US

Note: Data for China is average across prefecture cities (see definitions in Section 4.1 and data for US is from the State Expenditure Report of the National Association of Budget Officers.

To overcome identification challenges, I develop a novel instrument for local government spending using the fraction of unoccupied raw land in the city's downtown area in

2000, right before the formalization of the commercial land market in China. After 2000 with urban land sales becoming an important source of income for local governments, a higher fraction of unoccupied raw land means less compensation to incumbent occupants and hence higher profits for local governments. The fraction of unoccupied raw land appears to be orthogonal to various city characteristics in 2000 and only affects the economy through local government spending. With this instrument, I estimate the annual multiplier to be about 2 and the accumulative government spending multiplier to be about 14 at the prefecture city level. The multiplier is much larger for cities with higher GDP per capita or GDP growth before 2000, which is consistent with agglomeration rather than decreasing return to scale. There is no evidence that the magnitude of the multiplier depends on the benefit from WTO entry or the initial level of infrastructure. The firm-level evidence suggests that the local government spending has been productive. Higher government spending leads to an increase of material uses, resource utilization and productivity, and the effect is larger for industries that use more transportation services. As a result, firm entry also increases. I also find significant spillover effects within each city through technology spread and supply chain linkages.

I construct a comprehensive panel data set covering the prefecture city and sub-city level government budgetary expense, infrastructure investment and local economic conditions using various statistical yearbooks compiled by different central ministries. One city usually consists multiple sub-cities. Depending on the data availability, the city level data covers the period 1996-2019 while the sub-city level data cover 1991-2019 with three years gap between 1995-1997. To study the firm-level response of government spending, I use firm location, industry and entry and exit data from the Firm Registry Information collected by the Industrial and Commercial Bureau until 2017 and the financial statements from the Annual Survey of Industrial Firms during 1998-2007.

The empirical strategy draws insights from the government engagement in the land market. Due to the state ownership of urban construction land, local governments in China has relied heavily on land sales to finance urban development, a practice often referred to as "land finance" (Cao et al., 2008; Lin and Yi, 2011; Liu et al., 2014). The commercial land market was formalized around 2000, and since then land finance has gradually become an important source of income for local governments. One important feature of land finance is that the profitability of land sales depends on the availability of unoccupied raw land in the downtown area because expropriating occupied land for resale requires a fair amount of compensation to incumbent occupants. Therefore, cities

with a higher fraction of raw land in 2000 benefit more from the rise of the land market.

Building from the urban map data developed by Liu et al. (2018), I measure the fraction of unoccupied raw land ("*raw*" for short) in the estimated downtown area in 2000 for each city as well as the sub-city. Liu et al. (2018) classifies each small land parcel on Earth as covered with artificial construction or not, and I identify unoccupied raw land as those without artificial construction cover. Since the majority of land expropriation and sale occurs in the downtown area, I first estimate the downtown boundary as the large cluster of occupied land, and then calculate the fraction of unoccupied raw land within the estimated downtown boundary.

I start by showing the orthogonality of *raw* with a rich set of city characteristics in 2000. For measures of economic activities, after controlling for provincial heterogeneity with the province fixed effect, *raw* is not significantly correlated with log GDP, GDP in the secondary and tertiary sector, employment and the number of active manufacturing firms. For measures of government spending and initial infrastructure, there is no significant correlation between *raw* and log budgetary expense, infrastructure investment, road area, length of water supply and drainage pipelines, net land supply, and the size of land zoned as industrial and residential uses. There is also no significant correlation between *raw* and firm-level input uses, productivity and resource utilization measures. As I will use the difference-in-difference (DID) estimation strategy using *raw* as the treatment after 2000, I further show that cities with differential *raw* exhibit parallel trends before 2000 in all the aforementioned outcome variables. These results support the assumption that *raw* is an exogenous shock to the cities in 2000.

I then study the nature of the shock, i.e., is it a shock to the local government spending or does it capture some other shock? First, in the cross section of cities, higher *raw* leads to a higher fraction of land sale revenues to be spent in infrastructure investment, since a smaller fraction is required to compensate removed occupants; *raw* is also negatively correlated with the ratio between land expropriated with compensation and total land supplied, which is consistent with our conjecture.

Second, one big concern is that higher *raw* may imply more room for development, which can lead to economic growth through the land supply channel rather than through government spending. However, using DID estimation with the panel of cities, I find no significant treatment effect of *raw* on the net land supply, i.e., the annual land supply minus land expropriated scaled by the estimated downtown size in 2000. The result

suggests raw does not shift the government net land supply.

After introducing the identification strategy, I first study the treatment effect of raw on local government spending after 2000 in a DID estimation framework with city and province-by-year fixed effect. I define local government spending as the sum of budgetary expenses (financed by budgetary revenues plus central government transfers) and infrastructure investment minus the overlap. This measure includes infrastructure investment financed by net loan issuance, and excludes compensation expenses to removed occupants the operation of social security funds. There is a positive and significant effect of raw on the local government spending. A 1% increase of raw leads to an increase of accumulative government spending until 2019 by about 90 RMB per capita. One interesting dynamic pattern is that, when government spending increases by 1 RMB caused by the increase of raw, the marginal propensity to spend on infrastructure investment is as high as 50% in the earlier years and decreases over time. The decreasing trend likely represents less opportunities of infrastructure investment over time.

I then conduct reduced-form analysis to estimate the treatment effect of raw on the city's real GDP growth after 2000 in the same DID estimation framework for local government spending. The discussion of raw supports the assumption that raw is a valid instrument for local government spending after 2000. It is not only orthogonal to the city's initial economic conditions but also not affect the future growth path through net land supply. I further consider other potential shocks that raw may be correlated with. The first is China entry to WTO in 2001. I calculate two city-level measures of the WTO shock: one is the share of foreign capital and the other is the export/output ratio, both are ex-post measures in 2007. Second, as the country's economic growth accelerates after 2000, cities that are more pro-cyclical will grow faster. I calculate the cyclicality of each city by regressing the city's real GDP growth on the country's GDP growth using data before 2000. Allowing time-varying effect of the WTO shocks and cyclicality in the reduced-form analysis barely changes the treatment effect of raw on the city's real GDP growth.

To consider potential spillover effect across cities that may bias the estimated effect of raw, following the spatial literature, I construct $\mathtt{CitySpillover}$, which is the inverse-distance weighted average raw of other cities. Regardless of how I select neighboring cities to calculate $\mathtt{CitySpillover}$, there is no evidence of significant spillover effect after 2000.

Finally, I move to the estimation of government spending multiplier. Unlike a temporary government spending shock for which one can use VAR or local projection to trace the dynamic impulse response, raw induces a persistent effect on local government spending. To the extent that the current GDP is affected by all the past government spending, we need to consider all the past government spending in explaining the current economic growth. Following Munnell (1990), I assume the effect of government spending depreciates at the rate of d. I then regress the real GDP in year t on the net accumulative government spending until t, using raw as the instrument for the net accumulative government spending. With the estimates of annual government spending multiplier, I can then calculate the present value of accumulative multipliers over time. In my preferred specification, I set $d = 5\%$ and use the discount rate of 10%.

The annual fiscal multipliers are about 1 in during 2001-2004, grows close to 3 in 2005 and decreases gradually over time. During 2017-2019, the multiplier is slightly below 2. Under the discount rate of 10%, the present value of accumulative government spending has been stable around 14 during the whole period.

There is large heterogeneity of the multiplier across cities. When I divide cities into two groups based on their GDP per capita in 2000, the multiplier is about 3-4 times larger for cities with high GDP per capita than cities with low GDP per capita in 2000. The multiplier is also much larger for the group of cities with GDP growth between 1996-2000 higher than the medium. These results is consistent with agglomeration because in more developed cities or cities with greater growth potential, firms are more likely to enter and hence the marginal government spending can generate a bigger effect on the economy.

It is helpful to discuss the external validity as one may wonder if the estimates can be applied to other countries or other periods. First, as the timing of the treatment almost coincides with China's entry into WTO, the multiplier may depend on the WTO entry. However, the multipliers are slightly larger for cities in the inland provinces as compared to cities in the coastal provinces, although cities in the coastal provinces benefit much more from the WTO entry. Second, the multipliers do not depend on the initial quality of the transportation network either. When the divide cities based on either the total road area or road area per capita, the magnitude of the multipliers are similar.

While there is no evidence of spillover across cities, the local government spending may generate spillovers across sub-cities within the same city. After developing an econometric framework to reflect both the direct and spillover effect, I find positive

spillover effect across different sub-cities with high population density. For sub-cities with low population density, the increase of raw leads to a much smaller increase of government spending, which is not big enough to generate spillovers across sub-cities. For the group of sub-cities with high population density, about 45% of the total effect on GDP is direct effect of sub-city's spending on itself and the rest 55% is spillovers of one sub-city's spending on others.

Lastly, to understand the mechanism underlying the larger multiplier, I test the opposite predictions on the response of the labor market by the model of government investment versus consumption spending. The government consumption spending leads to negative wealth effect on households, and the rise of labor supply due to the wealth effect is the key mechanism that explains the increase of output. In contrast, government investment spending leads to higher productivity of labor which mitigates the negative wealth effect as well as higher labor demand. Using city-level panel, I show that raw leads to both higher employment and higher wages after 2000, suggesting the shift of labor demand curve that is consistent with the predictions of government investment model.

I then turn to firm-level evidence to show how firms benefit from the government spending. I first examine the extensive margin, i.e., firm entry. There is a significant and positive treatment effect of raw on the number of manufacturing firms, and the magnitude of the effect is very close to that on real GDP. A 1% increase of raw increases the number of manufacturers by 0.53% and the real GDP by about 0.47%. As firms will stay after entry, the effect on firm entry can explain why the effect of government spending has been so persistent.

The next question is, how does government spending lead to the increase of firms? To answer this question, I examine the intensive margin effect. Using data of industrial firms during 2001-2007, I estimate that a 1% increase of raw can increase the local firms' real output by 0.32%, and half of the effect is due to the increase of material uses, 1/4 is due to increase of resource utilization and the 1/4 due to the increase of productivity. Moreover, the effect is larger for industries that use more transportation services. These results suggests that government spending benefits local firms by increasing access to bigger market.

The firm-level evidence also sheds light on the channel of the spillover effects. The first is the spread of technology, which is bigger for firms that share similar production

technology as firms in the other sub-cities. The second is through input-output linkages as the spillover effect on firms' output is larger if the firm is more vertically connected to firms in the other sub-cities.

Literature Review. The paper is first related to the literature on government spending multiplier. As discussed by Ramey et al. (2020), both the mechanism and the magnitude of the effect of government spending depends on the economic setting, such as whether government spending is consumption or investment. In the neoclassic approach, government consumption reduces household wealth, who responds by raising their labor supply. The rise in labor supply induced by the wealth effect is the key mechanism by which an increase in government purchases raises output. In contrast, government investment increases the marginal output of capital and labor in the future, leading to higher labor demand and crowd-in of private capital. In the long run, the magnitude of the government investment spending is higher than that of the government consumption spending. The local spending multiplier may differ from the closed-economy multiplier for reasons such as spillovers and outside finance which imposes no direct wealth effect on local households.

The recent revival of research, as reviewed by Chodorow-Reich (2019), mostly focuses on the general local government spending in the US, which is plausibly dominated by government consumption as shown in Figure 1. For example, Adelino et al. (2017) study changes of local government spending induced by bond rating adjustment, and find the effect is through government demand in the non-tradable sector and transfers and grants to the education sector. The American Recovery and Reinvestment Act (ARRA), enacted in early 2009 in the depths of the Great Recession, used both transfers to local governments and government purchases to stimulate the economy. Researchers try to exploit the exogenous variation of certain components of the ARRA grants across different states and study the effect on state government spending and employment (Chodorow-Reich et al., 2012; Chhabra et al., 2018; Dupor and McCrory, 2018). Note that although the ARRA grants were notionally intended for specific categories of spending, states were capable of making the grants effectively fungible and the increase of local government spending was not limited to the targeted categories (Dupor, 2017; Chodorow-Reich et al., 2012). The fungibility is one of the reasons why papers that study the infrastructure portion of the ARRA barely find any significant effect on employment (Leduc and Wilson,

2017; Dupor, 2017; Garin, 2019).[1] Another strand of papers focus on a specific type of government consumption spending that is likely exogenous to local economic conditions, military purchases. Ramey and Shapiro (1998) studies the effect of US government military purchases using plausibly exogenous military shocks with the time series data, and Nakamura and Steinsson (2014) and Auerbach et al. (2020) study the cross sectional variation of government military purchases. Overall, Chodorow-Reich (2019) concludes the local government spending multiplier to be about 1.8.

Some earlier papers focus on the effect of government investment in public capital. With annual U.S. data during 1949-1985, Aschauer (1989) shows that while the flow of government consumption and military capital are not productive, the nonmilitary public capital is a significant input in the production function and has a high output elasticity of 0.39. Aschauer (1990) estimates that $1 increase of public infrastructure is associated with approximately $4 increase of annual output. After estimating the state-level stock of public capital during 1970-1986, Munnell (1990) estimates the output elasticity of public capital to be 0.15, half of the elasticity of private capital. Baxter and King (1993) constructs a neoclassical model and estimates that with the value of public capital productivity from Aschauer (1989), the government investment multiplier to be 13.02 when capital and labor responds to the permanent improvement of public capital.

The earlier research, however, all suffers from the endogeneity issue of public capital investment and the anticipation effect of future government spending (Ramey, 2011a). Little recent effort has been made towards better identification. Leduc and Wilson (2013) explores the mechanisms by which the federal highway grants are apportioned to states to construct forecasts of current and future highway grants for each state and year during 1993-2010. They then use the change of expected future highway grants as measure of shocks to state highway spending and analyze the dynamic impulse response of economic activities to the highway spending shocks. They find considerably larger multipliers: the average output multipliers over ten-year horizons to be 1.3, roughly 2.7 impact to 6.2 at peak. A more extensive literature has documented the causal effect of infrastructure on local economic activities, including highways (Fernald, 1999; Duranton and Turner, 2012; Duranton et al., 2014) and telecommunications (Roller and Waverman, 2001), though they do not give direct estimates of multipliers.

The paper fits into this literature by studying the government spending multiplier

[1]Other reasons include the delays between appropriations and actual outlays (Leeper et al., 2010), and the short horizon of these studies.

in a setting where local government spending loads more on investment, as shown in Figure 1. I develop a novel instrument that imposes persistent effect on government spending, allowing me to estimate the long-run effect of government spending. Moreover, local officials in China have a strong incentive to increase economic growth because their promotion along the political hierarchy is linked to the local economic performance (Maskin et al., 2000; Li and Zhou, 2005; Yu et al., 2016). As a result, the local officials may allocate resources in a better way to help economic growth. Very few studies has examined the magnitude of fiscal multiplier in China's context. Li and Zhou (2021) use changes of central ministers as exogenous variation in earmarked transfers received by prefectural city-level governments and find the spending multiplier above one. Unfortunately, only 11 out of more than 300 cities form the treatment in the paper and the identification assumption is not well defended. Using a panel vector autoregression (VAR) with provincial data, Wang and Wen (2019) estimate the local fiscal multiplier to be 2.83 in the short run and 6.51 in the long run, and Zhang (2020) finds that the 5-year accumulative fiscal multiplier to be about 3. However, as pointed out by Ramey (2011a,b), most changes in government spending are anticipated, which can invalidate inferences from procedures that do not account for anticipations. Causal inference using VAR cannot control for shocks that simultaneously affect government spending and economic growth either.

The international evidence based on settings involving government investment, especially using data from developing countries, has been sparse. Henry and Gardner (2019) survey evidence across numerous countries and conclude that in only a minority do infrastructure projects, such as paved roads and electricity, clear the required hurdles. Izquierdo et al. (2019) use a variety of identification methods with data from Europe, US and Argentina and find that the multiplier on public investment is very high in countries that start with low levels of public capital.

Second, to some extent, the effect of financial constraints of local governments in this paper is analogous to that of firms. The local governments behave like firms in the sense that they manage the cities and finance the investment in infrastructure and public capital with tax and land sale revenues as well as debt issuance (Tiebout, 1956; Boskin, 1973; Fisher, 2018), although their objective can be much more complex than maximizing profits. The firms' financial constraint, due to frictions in the financial markets (Jensen and Meckling, 1976; Myers and Majluf, 1984), distorts investment behaviors (Fazzari et al., 1987; Kaplan and Zingales, 1997; Zwick and Mahon, 2017; Whited, 1992). So does the government financial constraint. Despite the vast literature on corporate financial

constraints, few papers study the effect of the government financial constraint.

Third, the empirical strategy is based on the institutional background of "land financing" (He et al., 2022; Cao et al., 2008; Lin and Yi, 2011; Liu et al., 2014). In addition to tax revenues and central government transfers, the local governments rely heavily on the profit of selling land use rights to the market to finance their expenditure. The paper provides clean evidence on how the land finance has supported China's economic growth.

The rest of the paper is organized as follows. Section 2 describes the data, Section 3 introduces the identification strategy, Section 4 shows the estimation of local government spending multipliers, Section 5 shows evidence of spillovers within the city, Section 6 exploits firm-level evidence supporting that local government spending is productive, and Section 7 concludes.

2 Data

I construct a comprehensive data set about the government fiscal statements and economic conditions from various sources. China consists of 336 prefectural cities in 2019 and each city is further divided into three types of sub-cities (i.e., Xian, Xianjishi and Shixiaqu). The governments of Xian and Xianjishi enjoy a fair amount of independence in terms of local policies and finance, while the governments of each Shixiaqu are at the direct leadership of the city governments. Therefore, the statistic yearbooks usually group all the Shixiaqu within each city into one sub-city and report statistics for all the Shixiaqu as a whole. In 2019, there are 2215 sub-cities. I first collect the city and sub-city level economic variables, including GDP, GDP in the secondary and tertiary sector, population, budgetary expense and revenue from the annual Urban Statistic Yearbooks during 1996-2019, which are compiled by the National Bureau of Statistics (NBS). The city level data also includes other economic variables such as real estate investment and employment. Although not frequently, the geographic composition of cities and Shixiaqu vary over time. As the base year of the analysis in this paper is 2000, I adjust the data of GDP, population, budgetary expense and revenue based on the geographic boundary defined in 2000.

The budgetary expense and revenue data are often missing in the Urban Statistic Yearbooks in the early years. I complete it with data from the Fiscal Statistical Yearbook of all sub-cities during before 2008, which are compiled by the Treasury Department of the Ministry of Finance. The data includes detailed variables such as annual budgetary

revenues, expenditure and central transfers.

The urban infrastructure investment and land zoning data are from the Urban Construction Statistic Yearbook from 1991 to 2019, which are published by the Ministry of Housing and Urban-Rural Development. The data only covers the sub-cities of Shixiaqu and Xianjishi, not Xian. There are 667 of these sub-cities, and they account for about 80% of total GDP in 2019. I hand collect all the tables from the original files to ensure data accuracy. I do not find the yearbook for the year of 1995-1997.

The land supply data is compiled from various sources. The city level annual land supply data is from China's Land and Resources Statistical Yearbook from 1999 to 2016. For years of 2017-2019, I aggregate the transaction-level data from the Ministry of Natural Resources to the city-year level. For data on the sub-city level, I aggregate the transaction-level data to the sub-city-year level, which covers 2007-2019. The annual land expropriated with compensation is taken from the Urban Construction Statistic Yearbook on the sub-city level, and I aggregate it to the city level.

The firm level data are from the Annual Survey of Industrial Firms during 1998-2007 conducted by the NBS. The data includes all firms in the manufacturing, mining and utility sector with annual sales above a threshold. It contains detailed firm-level financial information and has been used widely in the literature.

Finally, to get the annual number of active firms at both the sub-city and city level, I use the Firm Registry data from the Industrial and Commercial Bureau, which hosts basic information such as industry, establishment date, exit date, and location for all firms in China. I identify firms in the manufacturing sector and and calculate the number of firms that have established and not yet exited for each year at both the sub-city and city level.

Table 1 describes all the data used in the paper, and Table A.1 in the appendix provides the definition of each variable.

Table 1: Summary Statistics

Panel A: City level data

Obs		Mean	Median	St. Dev.	Obs
City	raw	0.55	0.58	0.24	337
	InfraInvt2Sale	0.38	0.21	0.55	310
	landexp2supply	0.43	0.28	0.44	304
	logdebt2budg	2.13	2.15	0.63	185
	CitySpillover	0.54	0.55	0.05	337
	Cyclicality	1.328	1.378	5.632	284
City-Year	log(GDP)	6.42	6.42	1.26	6720
	log(GDP_sec)	5.62	5.69	1.34	6735
	log(GDP_ter)	5.42	5.37	1.36	6717
	log(GDP_nr)	6.38	6.38	1.19	6525
	log(Emp)	3.41	3.36	0.79	6104
	log(Wage)	9.95	10.01	0.89	6816
	log(POP)	5.84	5.89	0.70	6770
	log(#Mfr)	7.67	7.74	1.65	7401
	LandSupply	658.46	395.75	809.44	6595
	LandExp	280.01	72.00	1351.39	6604
	NetLandSupply	1.29	0.79	2.20	6465
	log(BudExp)	4.309	4.395	1.439	6799
	log(BudRev)	3.533	3.487	1.495	6775

Panel B: Sub-city level data

Obs		Mean	Median	St. Dev.	Obs
Subcity	raw	0.53	0.58	0.27	2227
	popden	0.04	0.02	0.12	2342
Subcity-Year	log(GDP)	3.98	4.00	1.51	51307
	log(POP)	3.71	3.79	0.89	52171
	log(InfraInvest)	9.85	9.85	1.93	16329
	log(TranspInvest)	8.94	8.91	2.13	16182
	log(Road)	5.73	5.65	1.16	16437
	log(WaterPipe)	5.79	5.71	1.15	14910
	log(DrainPipe)	5.27	5.17	1.25	16425
	log(#Mfr)	5.37	5.44	1.81	48053
	log(LandSupply)	3.79	3.97	1.63	29038
	log(LandPrice)	6.13	6.16	1.09	29038
	log(ConsLand)	3.41	3.28	0.97	15583
	log(ResLand)	2.27	2.16	0.98	15571
	log(IndLand)	1.61	1.54	1.23	15538

Panel C: Firm level data

Obs		Mean	Median	St. Dev.	Obs
Firm-Year	log(Capital)	8.31	8.26	1.74	1625648
	log(Labor)	4.58	4.51	1.13	1634431
	log(Material)	9.37	9.32	1.47	1619005
	log(Output)	9.19	9.25	1.56	744940
	log(Sale)	9.70	9.63	1.42	1619438

3 Identification Strategy

3.1 The "Land Finance" System

Local governments in China are financed by a combination of three income sources. In 2019, they receive 10 trillion RMB from local government budgetary revenues, 7.5 trillion RMB from the central government transfer payments, and 8 trillion RMB from local government-managed funds, of which 7.3 trillion RMB is from land sales.[2] The budgetary revenues consist of various taxes. The local government follows the uniform tax rates set by the central government and shares the tax revenues among different layers of the governments according to the scheme set by the central and provincial governments (He et al., 2022). The central government transfer system is designed to balance the government fiscal capacity across regions. The central government determines, for each tax item, how to split the taxes between itself and local governments. It then transfers part of its share of tax revenues to poor regions to maintain the fiscal condition of the local governments. The last component is sale revenues of urban construction land by the local governments. The sub-city government intermediates almost all transactions of urban construction land by taking either raw or occupied land, determining the land zoning, upgrading the surrounding facilities, and selling the land use rights to the market, such as industrial firms or real estate developers. Land sale revenues is not shared with the central government and mostly retained by the sub-city level governments. The practice of financing local government spending through land sales is usually referred to as "land

[2]See the Ministry of Finance's 2019 Report on the execution of the central and local budgets. Besides the aforementioned three sources, revenue of state capital operations is very small; revenue of social security funds is large but cannot be spent for other purposes except social security payments.

finance."

Land finance was first adopted in Shenzhen in 1980. When Shenzhen was promoted to be a "special zone" in 1979, it did not receive much financial support from the central government. The first challenge facing the local officials was how to finance the upgrade and construction of infrastructure. The director of the city's housing bureau, Mr. Jinxing Luo, came up with the idea of selling a land parcel to Mr. Tianjiu Liu, a businessman from Hong Kong, who then built the first commercial housing community in China's history, Donghuliyuan (Beautiful Garden around South Lake). The project turned out to be very successful as many people in Hong Kong had families in Shenzhen and they came to buy these houses for the family members. The profit from the land sale helped the city government build 240 apartments to accommodate government employees. One year later, Mr. Luo sold another five land parcels and raised 0.5B RMB, which was more than enough to finance all the infrastructure construction of the city's CBD at that time.

The wide adoption of land finance only began two decades later. The reform of Shenzhen was much ahead of most places in China. In 1980, houses were not yet private property and there was no commercial market for land either. Housing reform and the development of market-based houses in 1990s opened up land leases for the residential land market. The industrial and commercial land market also developed with the reform of state owned firms and the growth of private firms. However, regulations for the land market were not fully in place and there were substantial ambiguities in terms of how the land transactions should be organized. In 1999, the Ministry of Land and Resources issued the Notice of Encouraging Bidding and Auctions as Means of Land Use Right Transfers. In 2001, the State Council issued the Notice of Improving the Management of Land Resources, in which it mandates that all land supply plans shall be made public and all land transfers must be conducted with bidding or auction if there are more than one interested buyers. Such mandate was made law in 2002 and the land market finally formalized. The practice of land finance gradually became popular and has been widely used to finance local government spending, especially investment in local infrastructure.

The amount of land sale revenues is endogenous as it may depend on the extent of the local government financial constraint and investment opportunities. To exploit variation of land finance that is likely uncorrelated with local economic conditions, I rely on the feature that the profitability of land sales for local governments depends on the required cost to compensate incumbent occupants removed from the land. Overall,

the compensation cost as a share of total land sale revenues has been significant. He et al. (2022) estimate for the residential land, compensation cost is about 1/3 of sale revenues during 2007-2010. In 2014, the Ministry of Finance reports about 80% of land sale revenues were used to compensate incumbent occupants removed from the land in that year.

The compensation cost depends on the pre-occupancy status of the land within the downtown area. Land outside the downtown area are mostly classified as agriculture land and subject to strict restrictions from development to preserve food security. Therefore, the conditions of the landscape within the downtown area are most relevant for land financing. In the downtown area, the land can be classified into three categories. The first is occupied land with construction, the second is occupied raw land (i.e., without construction), and the third is unoccupied raw land. Taking the first type of land to resale is costly. In 2001, the State Council issued the Regulations on the Administration of Urban House Demolition and Relocation, of which the Article 24 mandates that the local governments must compensate the removed incumbent occupants a fair rate. For example, in 2004 Guangzhou set a lower limit on the compensation rate to incumbent occupants, which ranges between 1600 - 3000 RMB/m^2 for the core downtown area and 950 - 1150 RMB/m^2 for the peripheral downtown area. As comparison, the house price in Guangzhou in 2004 ranges about 3000-4000 RMB/m^2. Examples of the second type of land are grassland in a school or small farmlands surrounding the downtown area.[3] For this type of land, the government shall also compensate the occupants but at a much lower rate. In practice, the compensation is mostly linked to the area with construction.[4] The third type of land comes free to the government as there are no occupants to compensate. The compensation rate depends on the land zoning, but given the zoning, the relationship between the compensation rate and the pre-occupancy status holds regardless of the zoning. Therefore, the local governments benefit more from land sales if there is a larger fraction of raw land within the downtown area.

Inspired by this feature, the identification strategy in the empirical analysis is to exploit the cross-sectional variation of the fraction of raw land in each city's downtown area in 2000. I choose the year of 2000, right before the formalization of the land market,

[3]The protection of farmland only applies to those vast stretches of farmland defined as "basic farmland," not those segregated small pieces of farmland within the urban area.

[4]In the following sections, I will ignore the small difference between raw and unoccupied and use the two terms interchangeably.

to avoid issues with endogenous expansion of the downtown area after 2000.

3.2 Measure Raw Land in the Downtown

I measure the fraction of raw land in the city's downtown area in 2000 based on map data from a well cited paper by Liu et al. (2018), who use satellite images to classify every 30m×30m polygon on Earth as covered by impervious surface or not, where the impervious surface refers to pavement, concrete, brick, stone and other man-made impenetrable covers. Polygons identified as with impervious surface correspond to occupied land and those without impervious surface correspond to raw land in this paper. To estimate the downtown boundary, I rely on the fact that most of the developed and occupied lands are located in the downtown area while the suburban area mostly consists of farm land, forests and rivers. I can then estimate the downtown boundary based on the cluster of occupied land. Finally, I calculate the fraction of raw land within the estimated downtown boundary.

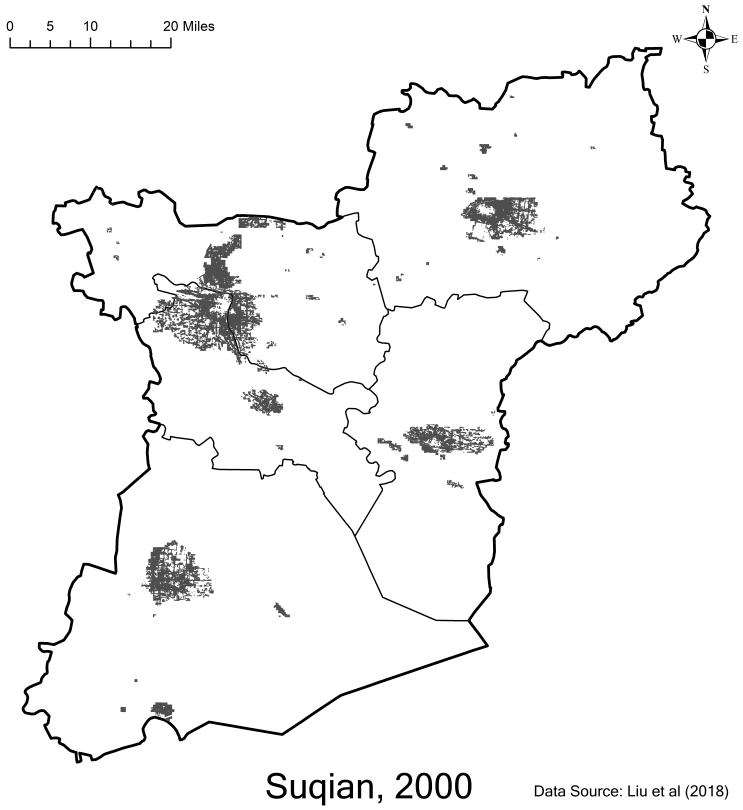


Figure 2: Geographical distribution of occupied land in Suqian, 2000

To illustrate the measurement, Figure 2 shows the geographic distribution of occupied land in the city of Suqian in 2000. The city consists of four sub-cities, including two Shixiaqu to the middle left and three other sub-cities. The dark area represents occupied land as identified with impervious surface by Liu et al. (2018). The occupied land forms four big clusters, which are perfectly in line with the downtown area of the four sub-cities. There are some extra small clusters that represent small developed towns not connected to the downtown area. The majority of the city was not developed and represents agriculture land, rivers, grassland, etc.

In Figure 3, I zoom in to take a close look at the center of Shuyang, which is the top-right sub-city in Figure 2. The first graph shows the distribution of occupied land. To estimate the downtown boundary, I aggregate all the polygons classified as with impervious surface by: (1) connecting any two neighboring polygons with distance less than one mile and (2) filling inside holes with area less than one square mile. The estimated downtown area is the colored area (green plus dark) shown in the second graph. The raw land within the downtown boundary is then the green area.[5]

Formally, I measurement the fraction of raw land within the city i's downtown area in 2000 as follows:

$$raw_c = \frac{\sum_i Raw_{c,i}}{\sum_i DownTown_{c,i}}, \tag{1}$$

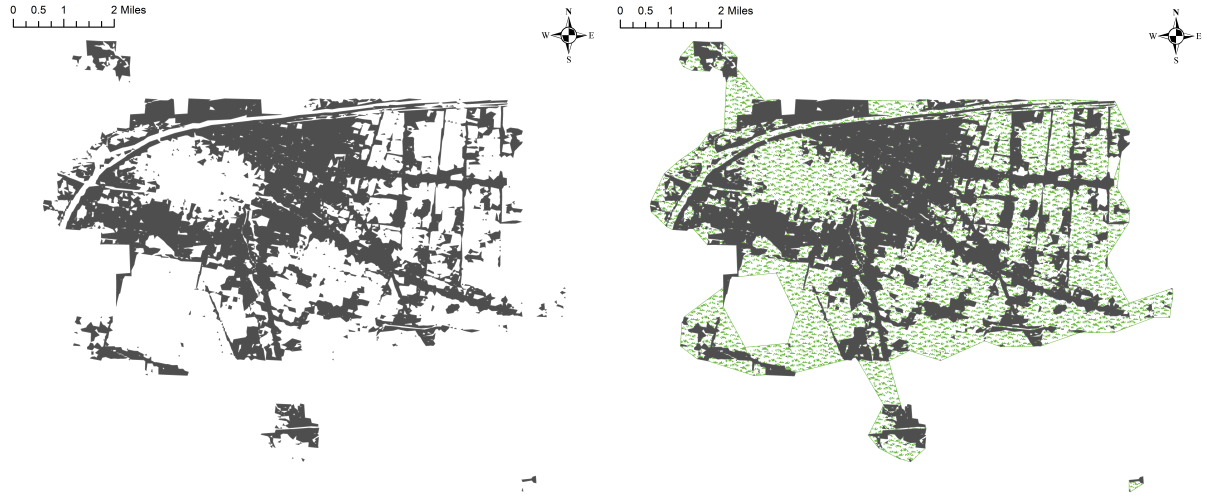
where $Raw_{c,i}$ is the size of raw land within the estimated downtown boundary of sub-city i in city c using the two procedures described above, and $DownTown_{c,i}$ is the size of the estimated downtown area of sub-city i in city c.

Similarly, I also calculate the fraction of raw land for each sub-city as follows:

$$raw_{c,i} = \frac{Raw_{c,i}}{DownTown_{c,i}} \tag{2}$$

Figure 4 compares the landscape of Shuyang between 2000 and 2015. First, the fraction of raw land has shrinked dramatically over time. In the first graph, the round green area on the top left used to be a piece of farmland has has been transformed into developed land, and the hexagon white area on the bottom left used to be the South Lake and

[5] I keep those small clusters not connected to the largest cluster in the calculation as land can also be supplied from these small towns. The empirical results using measures based on the single largest cluster for each sub-city barely change.



(a) Distribution of occupied land (b) Estimate downtown boundary

Figure 3: Estimating downtown boundary using occupied land for Shuyang

Note: The first graph shows the geographic distribution of occupied land of Shuyang in 2000; the second graph illustrates the estimation of its downtown boundary based on the geographic distribution of occupied land in 2000.

has been filled and built into a residential community. Second, the development of the downtown area until 2015 remains bounded by almost the same boundary as in 2000. This is consistent with the strict implementation of farmland protection that restricts the transform of farmland into urban construction land. Therefore, cities with less availability of raw land cannot simply turn to the raw land outside the downtown area.

3.3 The Orthogonality of raw

In the empirical analysis, I will use raw as an exogenous shock to the local government spending after 2000 in a Difference-in-difference estimation framework. In this section, I will show the orthogonality of raw against a rich set of local economic conditions in 2000 that may affect the future growth path, and the parallel trends of cities with differential raw before 2000 in various dimensions. The evidence supports the assumption that raw does not capture differential pre-trends and is an exogenous shock on the city's growth after 2000.

First, I examine the relationship between raw and various measures of economic

Shuyang, Suqian, 2000Data Source: Liu et al (2018)

Shuyang, Suqian, 2015Data Source: Liu et al (2018)

Figure 4: Estimated downtown boundary: 2000 vs 2015

activities and infrastructure in 2000. As some variables are at the city level and others are at the sub-city level for only part of the sub-cities, I run the following two regressions depending on what level the dependent variable is:

$$y_{c,2000} = \beta \times raw_c + \gamma_{p(c)} + \varepsilon_c \tag{3}$$

$$y_{c,i,2000} = \beta \times raw_{c,i} + \gamma_{p(c)} + \varepsilon_{c,i} \tag{4}$$

In Eq. (3) and (4), the LHS is the outcome variables in 2000 to be examined, $\gamma_{p(c)}$ controls for provincial heterogeneity, and ε_c and $\varepsilon_{c,i}$ are the random errors. In all the analysis in the paper, I control for provincial fixed effect for cross-sectional regressions and time-varying provincial fixed effect for panel regressions, due to the large heterogeneity across different provinces.

Table (2) reports the results. In Panel A, there is no significant correlation between raw with GDP, GDP in the secondary or tertiary sector, total employment or the number of manufacturing firms in 2000. In other words, cities with higher unoccupied land in the downtown area in 2000 did not start with lower level of economic development. The only variable that carries a significant correlation is total population size. A smaller total population likely leads to a smaller population in the downtown area and increases the fraction of unoccupied land size. If a smaller population reduces labor supply and negatively affects economic growth, then the estimated effect of local government

spending on economic growth using raw as the instrument will be downward biased.

In Panel B, I examine the correlation between raw and local government spending and infrastructure level. The budgetary expense and infrastructure investment are the two main categories of local government spending. The budgetary revenues are the tax revenues and administrative fees shared by all layers of governments within each prefecture city, and budgetary expenses are those financed by budgetary revenues and central government transfers. Part of the infrastructure investment is budgetary expense; a big portion is financed by the state-management funds dominated by the land sale revenues. In 2000, there is no significant correlation between raw with all three measures of local government incomes and spending. In Column (4)-(6), I examine the correlation between raw with the level of infrastructure, including total road area (Column (4)), the total length of water supply (Column (5)) and drainage pipelines (Column (6)). No significant correlation was found for any of them. Cities with differential raw land in 2000 do not start with differential flow of local government spending or level of infrastructure.

In Panel C, I look at the correlation between the sub-city's raw and local firm characteristics in 2000, including firms' productivity, input utilization, labor, capital and material. Appendix Section E provides details on the calculation of these firm characteristics. There is no significant correlation between firm characteristics with raw either.

In Panel D, I check the correlation between land supply and land zoning with raw. In Column (1), $NetLandSupply$ is total land supplied minus urban land expropriated scaled by the estimated downtown size, all measured in 2000. We can think of it as the land supply from the unoccupied raw land, but not necessarily from the downtown area. Higher raw is not significantly correlated with higher net land supply. In Column (2), there is no significant correlation between raw and total size of urban construction land either. In Column (3) and (4), I look at total land zoned as industrial and residential separately, and no significant correlation was found for either of them. In general, raw is not significantly correlated with land policies in 2000 that may put the city in a better position for economic growth after 2000.

As I use the DID estimation strategy for most analysis in this paper, I examine whether cities with differential raw had experienced parallel trends before 2000. The pre-parallel trends help support the identifying assumption for the DID estimation. That is, without the treatment, cities with differential raw would have evolved along the same trend, and hence the effect of raw reflects shocks due to the treatment.

Table 2: Correlation between *raw* and city characteristics in 2000

Panel A: City-level economic activities

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	log(GDP)	log(GDP_sec)	log(GDP_ter)	log(Emp)	log(#Mfr)	log(Pop)
raw	0.271	0.410	-0.047	-0.067	-0.392	-0.560**
	(0.972)	(1.258)	(-0.150)	(-0.265)	(-1.072)	(-2.379)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	273	273	256	332	279
R-squared	0.433	0.423	0.376	0.211	0.668	0.337

Panel B: Government spending and infrastructures

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	log(BugExp)	log(BugRev)	log(InfraInvt)	log(Road)	log(WaterPipe)	log(DrainPipe)
raw	0.116	0.419	0.177	-0.0913	0.0212	0.112
	(0.469)	(1.219)	(0.614)	(-0.496)	(0.100)	(0.526)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	278	630	633	633	632
R-squared	0.289	0.342	0.129	0.145	0.113	0.114
Obs	City	City	Subcity	Subcity	Subcity	Subcity

Panel C: Firm productivity, utilization and output

	(1)	(2)	(3)	(4)	(5)
Dep Var	tfpq	utilization	log(Labor)	log(Capital)	log(Material)
raw	-0.00649	0.0304	0.0543	0.123	0.197
	(-0.202)	(0.948)	(0.632)	(1.104)	(1.599)
Prov-Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	116,512	116,840	123,988	119,549	117,994
R-squared	0.246	0.255	0.249	0.183	0.211
Obs	Firm	Firm	Firm	Firm	Firm
#City	336	336	336	336	336

Panel D: Land supply and land zoning

	(1)	(2)	(3)	(4)
Dep Var	NetLandSupply	log(ConsLand)	log(IndLand)	log(ResLand)
raw	0.432	-0.136	-0.192	-0.117
	(1.238)	(-0.778)	(-0.884)	(-0.650)
Province FE	Yes	Yes	Yes	Yes
Observations	287	631	630	631
R-squared	0.235	0.071	0.085	0.104
Obs	City	Subcity	Subcity	Subcity

Note: Standard errors are clustered by cities in Panel C. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Depending on what level is the outcome variable on, I conduct the following DID estimation to examine the parallel trend assumption for various economic measures:

$$y_{c,t} = \sum_{\tau \neq 2000} \mathbb{1}_{t=\tau} \cdot \beta_\tau \cdot raw_c + \xi_t \cdot y_{c,2000} + \alpha_c + \gamma_{p(c),t} + \varepsilon_{c,t} \tag{5}$$

$$y_{c,i,t} = \sum_{\tau \neq 2000} \mathbb{1}_{t=\tau} \cdot \beta_\tau \cdot raw_{c,i} + \xi_t \cdot y_{c,i,2000} + \alpha_{c,i} + \gamma_{p(c),t} + \varepsilon_{c,i,t} \tag{6}$$

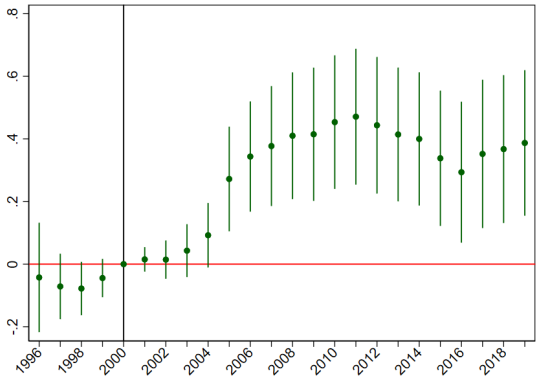
Figure 5 plots the 95% confidence interval of the β estimates for various y indicated under each graph. In Panel A, for either GDP, number of manufacturing firms or budgetary revenues and expenses, cities with differential treatment of raw exhibited parallel trends before 2000. In Panel B, I investigate government infrastructure investment, infrastructure investment in transportation, road area, the length of water supply pipelines, and industrial- and residential-zoned lands; all of them have exhibited parallel trends before 2000. The parallel trends along all these dimensions lend some support to the assumption that cities with differential raw would have experienced parallel growth path without the treatment. [6]

3.4 The Mechanism of the Effect of raw

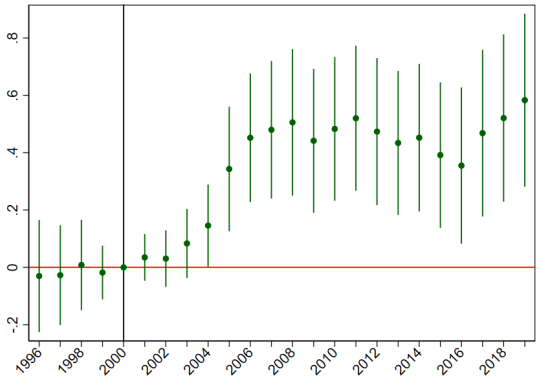
After showing evidence that raw appears as an exogenous shock in Section 3.3, I now discuss the nature of the shock, i.e., the mechanism through which raw affects future economic growth.

I first check if as conjectured, raw affects the required compensation to removed occupants and land sale profitability. The land sale revenues are mainly spent for two purposes: compensating removed occupants and financing infrastructure investment. Higher raw should imply less compensation to occupants and more to be spent on the infrastructure. In the data, I observe both the annual land sale revenues and the annual infrastructure investment financed by loan sales. As the compensation expense usually occurs before land sales, to mitigate the issue of time mismatch, I calculate the accumulative infrastructure investment financed by land sales and the accumulative land sale revenues during 2001-2005, and regress the ratio on raw, after controlling

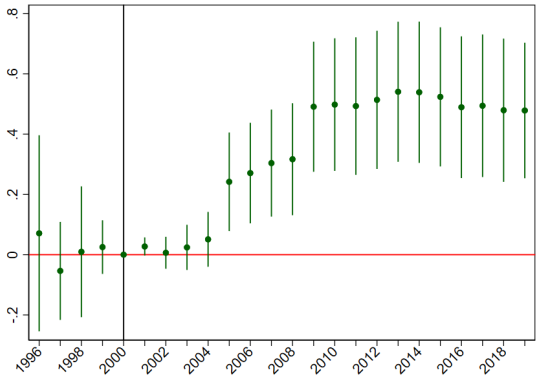
[6] Compared to Table 2, I do not report results for employment and population due to space limit, which are not the interested outcomes in this paper, but both exhibited parallel trends before 2000. Data for the length of drainage pipelines is sparse before 2000 and is ignored here.



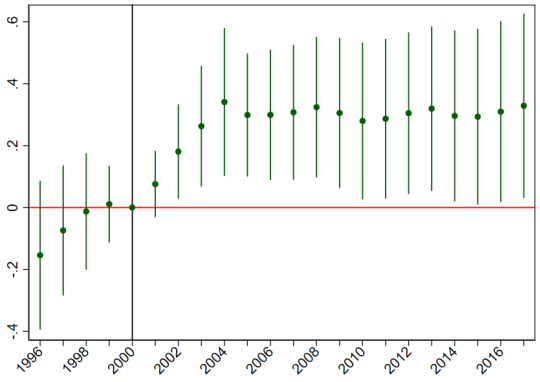
(a) $\log(GDP_{c,t})$



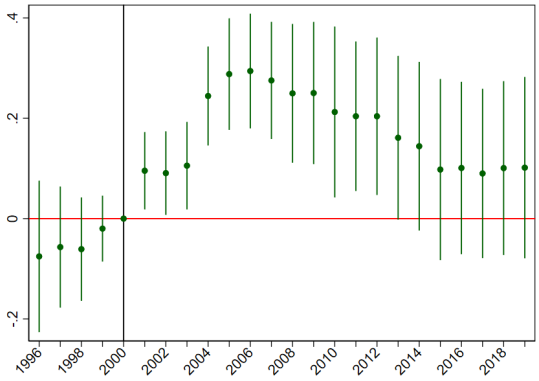
(b) $\log(GDP^{sec}_{c,t})$



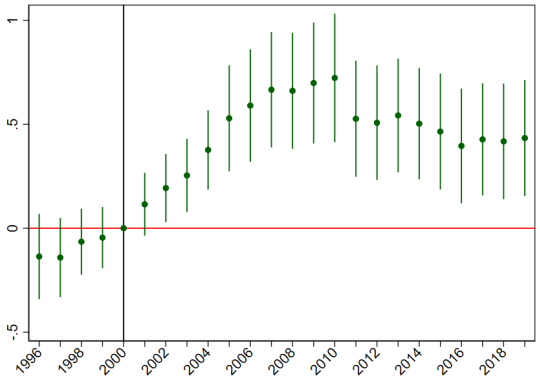
(c) $\log(GDP^{ter}_{c,t})$



(d) $\log(\#Mfr_{c,t})$

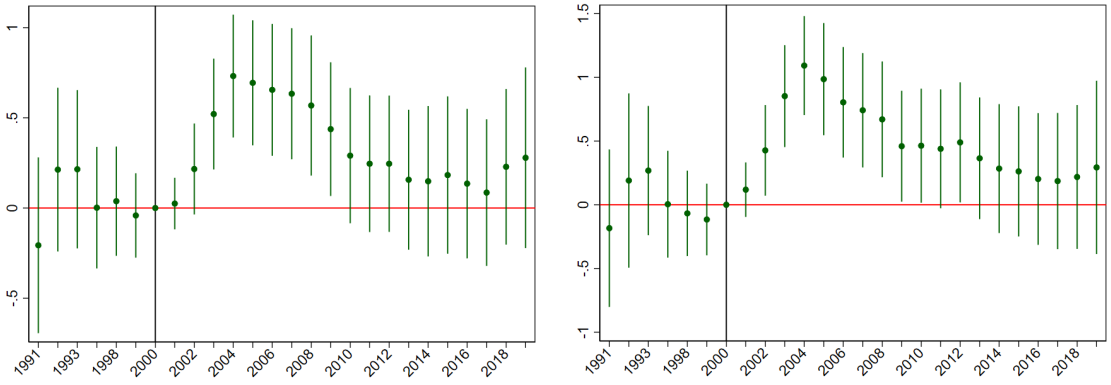


(e) $\log(BudExp^{ter}_{c,t})$

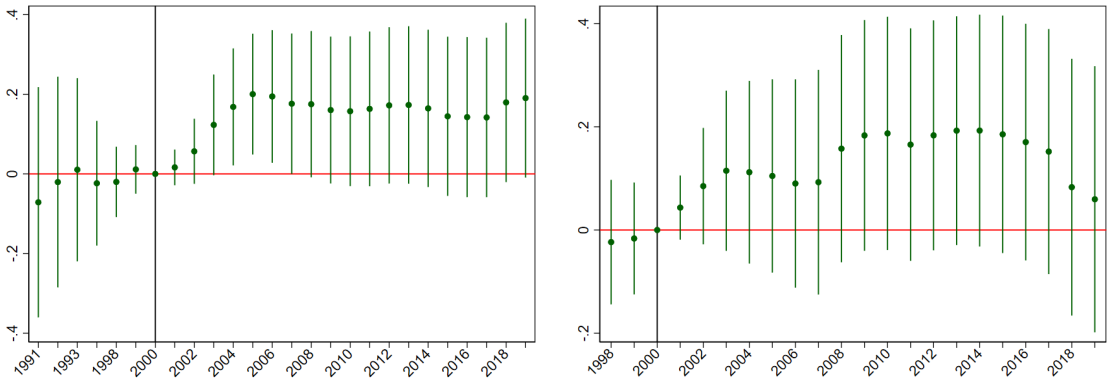


(f) $\log(BudRev_{c,t})$

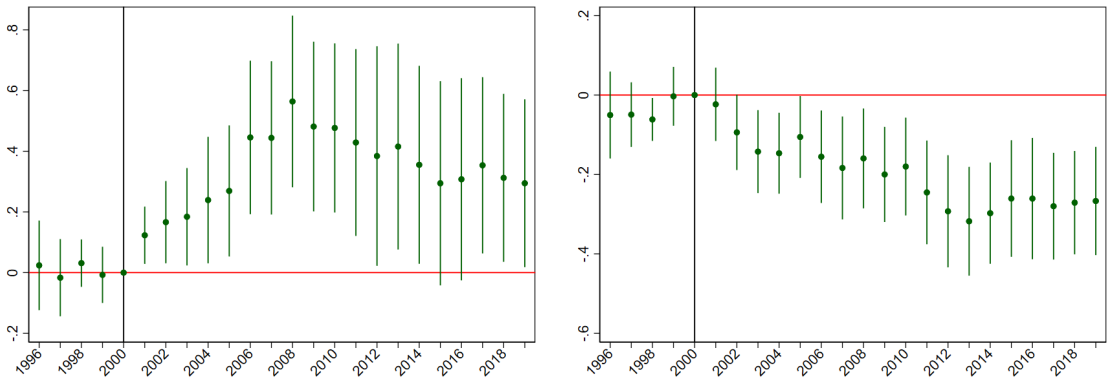
Panel A: City-level Economic Activities



(g) $\log(\text{GovtInvt}_{c,i,t})$ (h) $\log(\text{GovtInvt}^{tra}_{c,i,t})$



(i) $\log(\text{RoadArea}_{c,i,t})$ (j) $\log(\text{WaterPipe}_{c,i,t})$



(k) $\log(\text{IndZone}_{c,i,t})$ (l) $\log(\text{ResZone}_{c,i,t})$

Panel B: Sub-city level Infrastructure and land zoning

Figure 5: Parallel trend of cities and sub-cities with differential raw in various dimensions

Note: The figure plots the 95% confidence interval of the β estimates from Equation (5) and (6), where the dependent variable is indicated below each graph. All standard errors are clustered by the city or the sub-city, depending on the level of observations.

for provincial heterogeneity with province fixed effect.[7] Column (1) of Table 3 reports the results. As expected, higher raw implies the city can spend more on infrastructure investment for a given amount of land sale revenues since a smaller fraction is required to compensate the removed occupants.

We can also check for a given amount of land supplied, if higher raw is associated with a smaller fraction of land that comes with occupant compensation. I calculate the ratio between the size of urban land expropriated with occupant compensation during 2001-2016 and the size of total land supplied during 2004-2019, assuming a three-year lag between expropriation and supply, and regress it on raw after controlling for the province fixed effect. As expected, given the total size of land supplied, higher raw is associated with a significantly smaller fraction of land that requires compensation.

Table 3: City-level raw and land sale profitability

	(1)	(2)
Dep Var	InfraInvt2Sale	landexp2supply
raw	0.589***	-0.282*
	(3.128)	(-1.811)
Province FE	Yes	Yes
Observations	307	301
R-squared	0.336	0.218

Note: This table shows the correlation between the city's raw with the fraction of accumulative land sale revenues spent on urban infrastructure investment (Column (1)) and the ratio between accumulative land expropriated with compensation and land supplied (Column (2)). Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

With the effect on land sale profitability, raw will affect local government spending. One concern for this interpretation is that a higher fraction of raw may also imply more room for development within the downtown area. The argument is based on the conjecture that raw affects net land supply, i.e., the supply of previous unoccupied land.

To check if this conjecture is true, I calculate $\mathtt{NetLandSupply}$ for each city during 1999-2019, and estimate the treatment effect of raw on $\mathtt{NetLandSupply}$ using Equation

[7] I choose the period of 2001-2005 to better match the numerator with the denominator. In the data, I can only observe total infrastructure investment financed by contemporaneous land sale revenues and loans backed by future land sales; before 2005, the portion financed by loans is likely small and the portion financed by contemporaneous land sales dominates, which better matches the land sale revenues during 2001-2005.

(5). I scale the net land supplied by the estimated downtown area instead of taking the log value, as I do for all other outcome variables, because the annual net land supplied can be negative. Figure 6 plots the 95% confidence interval of the β estimates. Not only are the coefficient estimates insignificant, there is also no obvious trend as the coefficient fluctuates around zero. The result rejects the conjecture that raw affects future growth by increasing net land supply. [8]

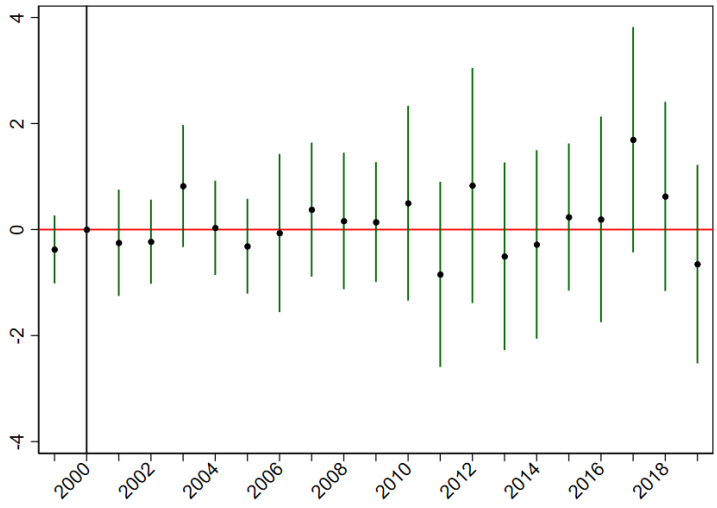


Figure 6: The treatment effect of raw on net land supply

Note: The graph plots the 95% confidence interval of the β estimates from Equation (5), where the dependent variable is anual net land supply, i.e., total land supply minus land expropriated scaled by the estimated downtown size in 2000.

To conclude, I construct a variable of raw that affects the profitability of the land sales for local governments after 2000, when the commercial land market in China was formalized. The variable is not correlated with any initial economic conditions of the city in 2000 (except population) or growth of economic activities of the city before 2000, and it does not affect future growth through land supply. In the next section, I will study its effect on local government spending and establish the causal effect of local government spending on economic growth.

[8] Despite no significant effect on the total land supply, raw affects the government land zoning decisions through its financial constraint. As pointed out by He et al. (2022), the local government land zoning decisions involve an intertemporal trade-offs. Industrial land pays more tax revenues in the future, but lower upfront land sale revenues as compared to residential land. A higher value of raw relaxes the government financial constraint and leads a shift of land zoning from residential to industrial. See Appendix Section B for more results on land zoning.

4 Local Government Spending Multiplier

This section reports how I estimate the local government spending multiplier. I first document patterns of the marginal increase of local government spending over time and across categories when its financial constraint is relaxed due to raw, then show the reduced form regressions of log(GDP) on raw to discuss the identifying assumptions, and lastly conduct the estimation of multipliers.

4.1 Local Government Spending

I start with the definition of local government spending. Figure 6 illustrates the relationship between different concepts. As I describe in Section 3.1, the local governments are financed by three income sources: budgetary revenues, central government transfer payments, and land sale revenues. I also list the net debt issuance as one income source. The budgetary revenues and central transfers are used for budgetary expenses, which includes part of the infrastructure investment. The land sale revenues are spent for compensation to removed occupants and infrastructure investment. I define total local government spending as the sum of the budgetary expense and infrastructure investment minus the overlap, and divide it into two components: infrastructure and other spending.

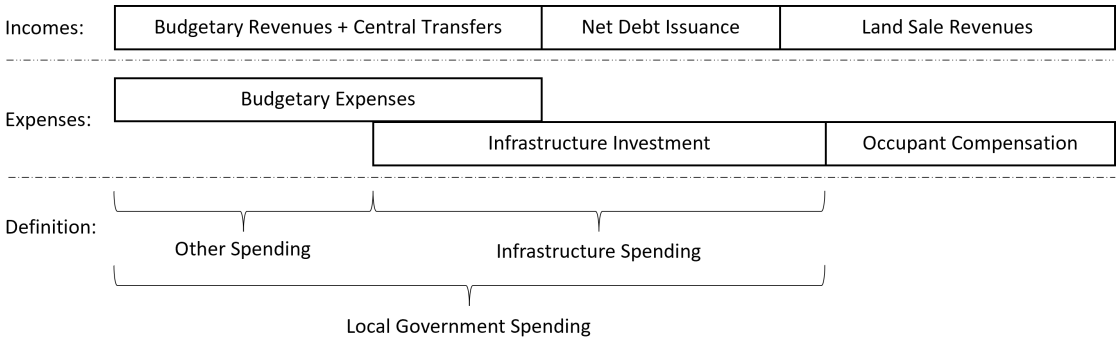


Figure 7: Definition of local government spending

Unlike a temporary fiscal stimulus that leads to a one-time shock to local government spending, raw will generate a persistent effect on local government spending through two channels. The first is the direct effect on occupant compensation cost. The effect is persistent because local governments will supply land and compensate occupants

gradually over a long horizon. The process is still going on until 2022, although many believe it has approached the end. The second is the indirect effect on future tax revenues due to realized economic growth.

As shown in Figure 5 Panel A, there is a persistent and positive effect of raw on the city's budgetary revenue. The effect on the budgetary expense is also significant and positive in the early years, and diminishes over time after 2006 and becomes positive but insignificant since 2014, while the effect on budgetary revenue remains significantly positive. The difference is driven by the central government transfers. The different pattern between budgetary expenses and revenues suggests that the central government becomes aware of the fiscal inequality across local administrations due to raw, and responds by increasing transfers to places at an inferior position in land finance (i.e., lower raw).

In Figure 5 Panel B, there is a significant and positive effect of raw on the flow of infrastructure investment in the early years, and the effect becomes insignificant after 2010. The insignificance after 2010 could be explained by the central government transfers. Another reason is the relaxation of local government debt issuance after 2010 (Chen et al., 2021). Appendix Section 3 shows that there is a large and negative correlation between raw and the city's debt balance in 2017. That is, cities at an inferior position issued more debt after 2010.

The persistence of the effect on local government spending imposes one challenge to the estimation of government spending multiplier. For a one-time shock to local government spending, one can use VAR and local projection to trace the dynamic impulse response. For a persistent change of local government spending, all the past government spending can affect current economic growth. Ideally for any year t, one should allow differential effect of government spending occurred in different previous year $\tau \leqslant t$. However, as raw is constant for each city, it is impossible to exploit exogenous variation of local government spending over time and hence I cannot estimate the effect on GDP in year t for different τ separately. Following Cook et al. (1990), I will assume a constant depreciation rate d of government spending. That is, 1 RMB of local government spending in year τ has the same effect on real GDP in year t as d RMB of local government spending in year $\tau + 1$. In the next section, I try different values of d to see how it affects the estimated multiplier. For now, let us assume $d = 5\%$.

Define the accumulative net real government spending until year t as follows:

$$AG_c^t = \sum_{1998 \leqslant t' \leqslant t} G_{c,t'} \times (1-d)^{t-t'}, \tag{7}$$

where $G_{c,t}$ is real local government spending in city c and year t, which equals the nominal local government spending as defined in Figure 7 divided by GDP deflator index (normalized to be 1 in 2000). I choose the starting year to be 1998 because it is the first year for which I observe both budgetary expense and infrastructure investment so that I can calculate $G_{c,t'}$. I define accumulative net real infrastructure spending and accumulative net other spending in a similar way.

To examine the effect of raw on accumulative real government spending, I first conduct the following DID estimation on the panel of cities during 1998-2019:

$$\log(AG_c^t) = \sum_{\tau \neq 2000} \beta_\tau \cdot \mathbb{1}_{t=\tau} \cdot raw_c + X_{c,2000} \cdot \Gamma_t + \alpha_c + \gamma_{p(c),t} + \varepsilon_{c,t}, \tag{8}$$

where $X_{c,2000} = (\log(AG_c^{2000}, \log(GDP_{c,t}))$[9]. The inclusion of the time-varying effect of $X_{c,2000}$ is to be in line with the following multiplier estimation specification and reduce standard errors and increase statistical power of the test; it barely changes the magnitude of the estimates β_τ.

After estimating the parameters in Equation (8), I then calculate the marginal increase of AG_c^t for $t > 2000$ when raw_c increases by 1%:

$$\begin{aligned} \Delta\hat{AG}_c^t = &\exp\left(\hat{\beta}_t \cdot (raw_c + 1\%) + X_{c,2000} \cdot \hat{\Gamma}_t + \hat{\alpha}_c + \hat{\gamma}_{p(c),t}\right) \\ &- \exp\left(\hat{\beta}_t \cdot raw_c + X_{c,2000} \cdot \hat{\Gamma}_t + \hat{\alpha}_c + \hat{\gamma}_{p(c),t}\right) \end{aligned} \tag{9}$$

The average effect per person is then given by $\mathbb{E}[\frac{\Delta\hat{AG}_c^t}{Pop_{c,t}}]$.

I conduct the estimation of the average effect for local government infrastructure and other spending separately. The left panel of Figure 8 plots the average effect per person for the two types of spending since 2001. The effect on other spending has grown steady over time to about 80 RMB/person in 2019. The effect on infrastructure investment peaked around 2012 at about 15 RMB/person and has been stable ever since. As I explain

[9]GDP is real value using nominal value divided by the GDP deflator index normalized to be 1 in 2000.

before, this is likely caused by the substitution of central transfers and debt issuance for land sale profits after 2012.

The right panel of Figure 8 plots the average ratio between the increase of infrastructure spending and the increase of total local government spending. In the first four years, for every one RMB increase of total local government spending, roughly 0.4-0.45 RMB was spent on infrastructure investment. The ratio decreases over time. In 2019, the local governments allocate every extra one RMB into infrastructure and other spending proportional to the share of the two types of spending. The decreasing trend is likely to be driven by the decrease of return from infrastructure investment. It may be very profitable to increase the highway from 0 to 1. But with an existing highway, the marginal return from building another one might be low.

Figure 8: Marginal Effect of raw on City Government Spending

Note: The first graph shows the average marginal increase of accumulative government investment and other spending when raw increases by 1%. The second plots the ratio of the marginal increase between accumulative government investment and total spending, along with the ratio of the total accumulative government investment and total spending.

4.2 Identification Assumptions

Before going to the estimation of local government spending multiplier, I summarize the identification assumptions in this section and provide additional tests to address some

concerns in interpreting the effect of raw.

Formally, consider the following specification about the effect of raw on the city's GDP growth:

$$\log(GDP_{c,t}) = \beta \cdot \mathbb{1}_{t>2000} \cdot raw_c + \alpha_c + \gamma_{p(c),t} + X_c \cdot \Gamma_t + \varepsilon_{c,t}, \tag{10}$$

where $GDP_{c,t}$ is real GDP (using the price of 2000) of city c in year t, α_c captures time-invariant city fixed effect, $\gamma_{p(c),t}$ controls for time-varying provincial shocks, X_c is set of city characteristics, and $\varepsilon_{c,t}$ is the stochastic errors.

For β to represent the causal effect of raw_c on $\log(GDP_{c,t})$ through local government spending, we need the assumption that

$$\mathbf{E}\left[\mathbb{1}_{t>2000} \cdot raw_c \cdot \varepsilon_{c,t}\right] = 0 \iff \mathbf{E}\left[raw_c \cdot \varepsilon_{c,t}\right] = 0, \ \forall t > 2001 \tag{11}$$

Assume the following process for the error term:

$$\varepsilon_{c,t} = f(\varepsilon_{c,t-1}) + \eta_{c,t}$$

The violation of the Condition (11) can be caused by either $\mathbf{E}[raw_c \cdot \varepsilon_{c,2000}] \neq 0$ or $\mathbf{E}[raw_c \cdot \eta_{c,t}] \neq 0$ for $t > 2000$. The parallel trends of cities with differential raw_c in various dimensions in Figure 5 suggests $\mathbf{E}[raw_c \cdot \varepsilon_{c,2000}] \neq 0$ is not likely to hold. In Section 3.4, I also show raw_c does not lead to more net land supply after 2000, so net land supply is not a candidate for η_t to violate the identification assumptions.

However, to make sure raw_c does not happen to pick up some shocks after 2000, I include various controls in X_c and allow its effect to be time-varying. The first is China's entry to WTO in 2001. I construct two ex-post measures of exposure to WTO shock at the city-level: the export/output ratio in 2007, and the share of foreign capital among all manufacturing firms in 2007. Using ex-post measures may lead to over-control if raw_c affects the city's benefit from WTO entry.

Second, the economic reforms and entry to WTO led to high GDP growth for China, and cities that are more pro-cyclical would experience higher economic growth. I then construct a city-level cyclicality measure, by regressing the city's annual real GDP growth on the country's annual real GDP growth using data during 1996-2000.[10]

[10]Thanks Ralph S. J Koijen for this suggestion.

Third, higher raw may lead to more real estate construction on the raw land. To exclude the mechanism effect on GDP through real estate investment, I deduct real estate investment from GDP.

Lastly, in case of spillover effect across cities, η_t may capture the spillover effect from neighboring cities. If raw_c between neighboring cities is correlated, then η_t would be correlated with raw_c, which would bias the estimates of β. To this end, following the spatial economics literature, I construct the inverse-distance weighted average raw_c of other cities for each city c, $CitySpillover_c$.

Table 4 reports the estimation results. In Column (1), I report the estimation results without any controls of X_c. In Column (2), I include $\log(AG_c^{2000})$ and $\log(GDP_{c,2000})$ to control for differential growth path for cities with different starting point. The coefficient estimates barely change. When the two measures of WTO shock are added in Column (3) and the measure of cyclicality is added in Column (4), the coefficient estimates barely change either. In Column (5), I deduct the real estimate investment from GDP and use its log value as the dependent variable. the coefficient estimate increases slightly but the implied average dollar effect barely change.

In the last four columns in Table 4, I try four different measures of across-city spillovers. The first is the inverse-distance weighted average raw_c of all other cities in China. The second is based on only those with population density above the median.[11] The third measure is based on cities within the distance of 500 km. Cities more than 500 km away are likely to exert zero effect. The last is based on cities with both population density above median and distance within 500 km. There is no evidence of across-city spillovers regardless of the measure of spillovers.

To sum, the effect of raw_c on the city's GDP growth is causal and the effect is through local government spending rather than picking up some other city-level shocks after 2000.

4.3 Estimation of Government Spending Multiplier

Having established the results from the previous two sections, the estimation of local spending multiplier is then straightforward using the following two-step procedures. First, as we use the year of 2000 as the base year and allow flexible time-varying effect

[11] In Section 5, I will show how the spillover effects within the city depends on the population density. So one reasonable conjecture is that the across-city spillover may also depend on the population density.

Table 4: Treatment Effect of raw on the city's GDP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep Var	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP_nr)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
$\mathbb{1}_{t>2000} \cdot raw$	0.350***	0.370***	0.348***	0.345***	0.402***	0.324***	0.351***	0.321***	0.356***
	(3.739)	(4.228)	(3.929)	(3.868)	(4.999)	(2.738)	(2.917)	(2.815)	(3.190)
$\mathbb{1}_{t>2000} \cdot CitySpillover$						0.301	-0.0878	0.128	-0.102
						(0.371)	(-0.106)	(0.417)	(-0.295)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base Year Effect	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WTO Shock	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclicality	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,603	6,587	6,587	6,587	6,383	6,587	6,587	6,587	6,587
R-squared	0.989	0.990	0.991	0.991	0.988	0.991	0.991	0.991	0.991
#City	279	278	278	278	278	278	278	278	278

Note: This table shows the treatment effect of raw on the city's GDP growth after 2000. I add time-varying effect of log(GDP) in 2000 from Column (2), the WTO shock from Column (3), a cyclicality measure from Column (4), and deduct real estate investment from real GDP in Column (5). I include different measures of cityspillover in the last four columns: Column (6) is based on all other cities, (7) based on cities with central sub-city's population density in 2000 above median, (8) based on cities within 500km away, and (9) based on cities with both population density higher than median and distance smaller than 500km. Standard errors are clustered by cities. T-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of the base year's $\log(GDP_{c,2000})$ and $\log(AG_c^{2000})$, we conduct the following Two-Stage Least Squares estimation where $\log(AG_c^t)$ is instrumented by raw_c:

$$\log(GDP_{c,t}) = \beta_t \cdot \log(AG_c^t) + \gamma_{p(c),t} + X_{c,2000} \cdot \Gamma_t + \varepsilon_{c,t}, \tag{12}$$

where $GDP_{c,t}$ is real GDP using the price in 2000, AG_c^t is defined by Equation (7), $\gamma_{p(c),t}$ captures time-varying provincial shocks, and $X_{c,2000} = (\log(GDP_{c,2000}), \log(AG_c^{2000}))$.

Second, with the estimates from Equation (12), I can then calculate the annual spending multiplier in year t as follows:

$$\begin{aligned} M_t = \frac{1}{N} \sum_c \Big[&\exp\left(\hat{\beta}_t \cdot \log(G_c^t + 1\text{m RMB}) + \hat{\gamma}_{p(c),t} + X_{c,2000} \cdot \hat{\Gamma}_t\right) \\ &- \exp\left(\hat{\beta}_t \cdot \log(G_c^t) + \hat{\gamma}_{p(c),t} + X_{c,2000} \cdot \hat{\Gamma}_t\right)\Big] \end{aligned} \tag{13}$$

The present value of accumulative multiplier for 1 RMB spending in year t is then:

$$PV_t = \sum_{t' \geqslant t} M_t \cdot \left(\frac{1-d}{1+R}\right)^{t'-t} \tag{14}$$

As my sample ends in 2019, I cannot estimate M_t for $t > 2019$. However, the estimated M_t is very stable during 2018-2019 and I use the simple assumption that $M_t = M_{2019}$ for $t > 2019$.

To conduct the estimation, we still need two parameters: d and R. He et al. (2022) estimates the return from supply industrial land for governments is about 10% in 2007. As the average term of city mayors is about five years, they could be myopic and have a high discount rate for the future. As a result, I will use $R = 10\%$ in this paper. The choice of R does not affect the estimation but only the calculation of PV_t. One can easily compute PV_t using Equation (14) with any preferred value for R.

The impact of d on PV_t is ambiguous. On one hand, a higher value for d will lead to a smaller value of AG_c^t and hence a larger value for β_t and M_t. On the other hand, higher d means faster diminishing of the effect of previous spending. To see if the results are sensitive to the choice of d, I try different values of d ranging from 5% to 40%. Figure 9 reports the time series of $\{PV_t\}$ for different choice of d.

First, d has different impact on the estimates of PV_t in earlier years and later years.

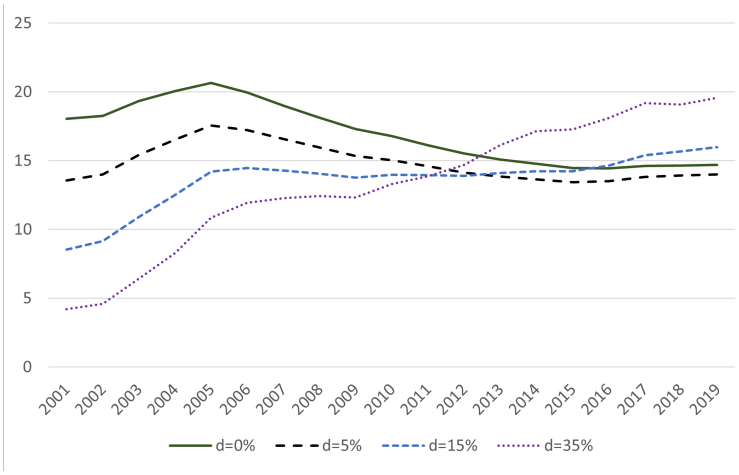


Figure 9: Present value of local govt spending multiplier

Note: The figure plots for each year, the present value of accumulative local government spending multiplier calculated with different values of depreciation rate d.

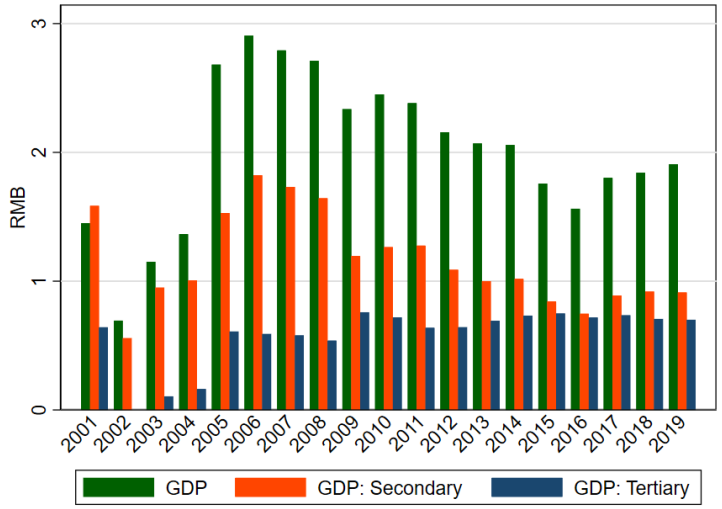


Figure 10: Local govt spending multiplier over time

Note: The figure plots the annual local government spending multiplier, i.e., the increase of real GDP in that year for a one RMB increase of net accumulative government spending calculated at the annual depreciation rate of 5%.

When d increases, PV_t tends to decrease for $t < 2010$ and increase for $t > 2010$. As a result, the time trend of PV_t goes from decreasing to increasing. If we believe government spending in the earlier years should generate higher return, then it is more likely that $d < 15\%$. Second, for $d < 15\%$, the estimated PV_t would vary between 10 and 20 in the earlier years, and fluctuate within a tight range around 15. In terms of PV_t, the value of d does not seem to matter very much. For the rest of the paper, I will stick to $d = 5\%$. All the discussion below in this section is robust to alternative values of $d < 15\%$.

Under $d = 5\%$, the annual spending multiplier, M_t, is shown in Figure 10. The annual spending multipliers are very small in the first four years, probably due to a lag of economic response to local government spending. It then rise to above 2 in 2005 and slowly decreases over time. In 2019, the multiplier is slightly below 2.

To see the effect on the secondary and tertiary sectors, I replace GDP with GDP of the secondary and tertiary sector in the two-step estimation. In the earlier years, the effect is almost all driven by the secondary sector. The effect on the tertiary sector gradually increases and is about the same magnitude as the secondary sector in 2019. The effect is almost all borne by the secondary and tertiary sector, and the residual effect on the primary sector is almost zero.

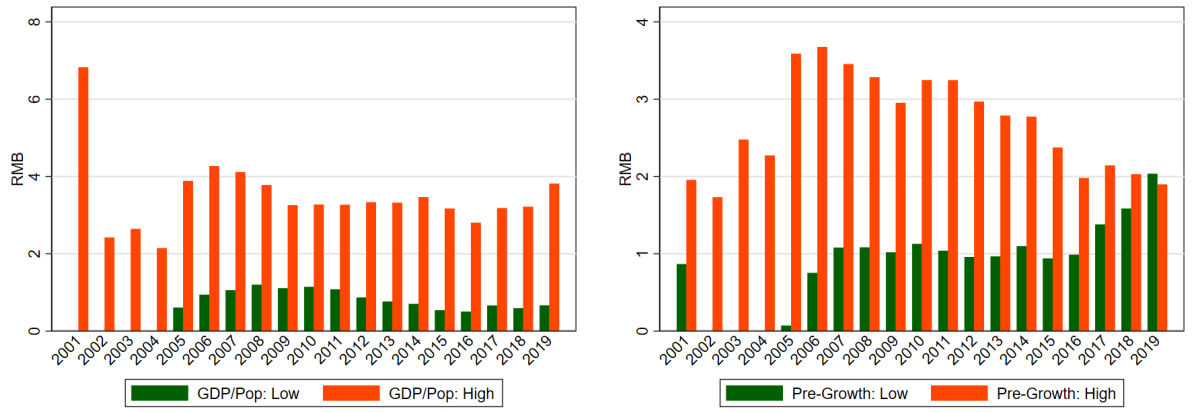
4.4 Heterogeneity of Government Spending Multipliers

In this section, I exploit how the local government spending multipliers depend on the initial status of the local economy, as has been heavily discussed in the literature.

The initial economic growth. In case the government spending affects output demand but does not affect the production directly, which is the setting studied by most papers on local government spending multiplier after the recession, the multiplier tends to be larger during recessions than in booms. In my context where local government spending is more likely to affect the production side of the economy, the effect may depend on the initial level of economic development.

To check the heterogeneity with respect to the city's initial economic development in 2000, I divide the cities into two equal groups based on: (1) GDP per capita in 2000; (2) the real growth of GDP from 1996 to 2000. I then conduct the two-step estimation procedures described in Section 4.3 for each group separately. Figure 11 shows the estimated annual

spending multiplier for each group over time. The multipliers are much larger for cities with higher GDP per capita in 2000 or higher GDP growth before 2000. This is in contrast to the findings in the literature that government spending multiplier tends to be larger during recessions than booms. The result is, however, consistent with agglomeration. As I will show later, the larger multiplier is mostly driven by new firm entries. In cities with higher economic development or greater growth potentials, firms are more likely to enter, and hence the marginal government spending by these cities can lead to larger multiplier effect.



(a) GDP per capita in 2000 (b) GDP growth from 1996 to 2000

Figure 11: Local govt spending multiplier and economic development

Note: The figure plots the annual local government spending multiplier for cities with different level of economic development. The multiplier is the increase of real GDP in that year for a one RMB increase of net accumulative government spending calculated at the annual depreciation rate of 5%. The first graph groups cities by their GDP per capita in 2000; the second graph groups cities by the GDP growth from 1996 to 2000.

The WTO shock. As the timing of the treatment coincides with China's entry to WTO in 2001, one natural conjecture is that the magnitude of the multiplier may depend on the WTO event. Without China's entry to WTO, the local government spending multiplier might not have been so high. To give some evidence on whether this is true, I conduct the two-step estimation procedures for inland and coastal provinces separately. Cities in the coastal provinces benefit much more from WTO entry than inland cities. For example, in 2007, the average share of foreign capital across cities is about 24.6% for cities in the coastal provinces as compared to 10.6% for cities in the inland provinces, and the average

export/output ratio is about 27.4% for cities in the coastal provinces, as compared to 9.7% for cities in the inland provinces.

Figure 12 shows despite the large difference in the benefit from WTO, the local government spending multipliers are very similar between coastal and inland provinces. If any difference, the multiplier seems to be larger for the inland provinces than the coastal provinces.

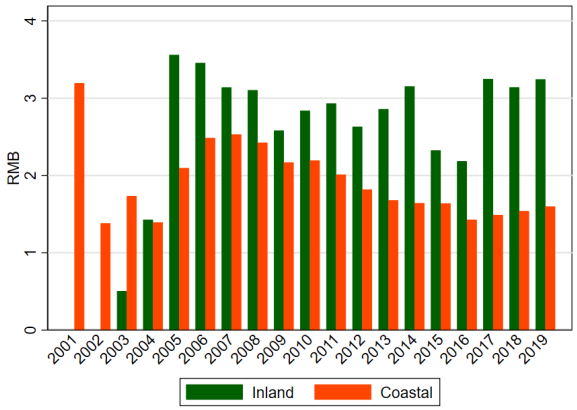


Figure 12: Local govt spending multiplier: coastal versus inland

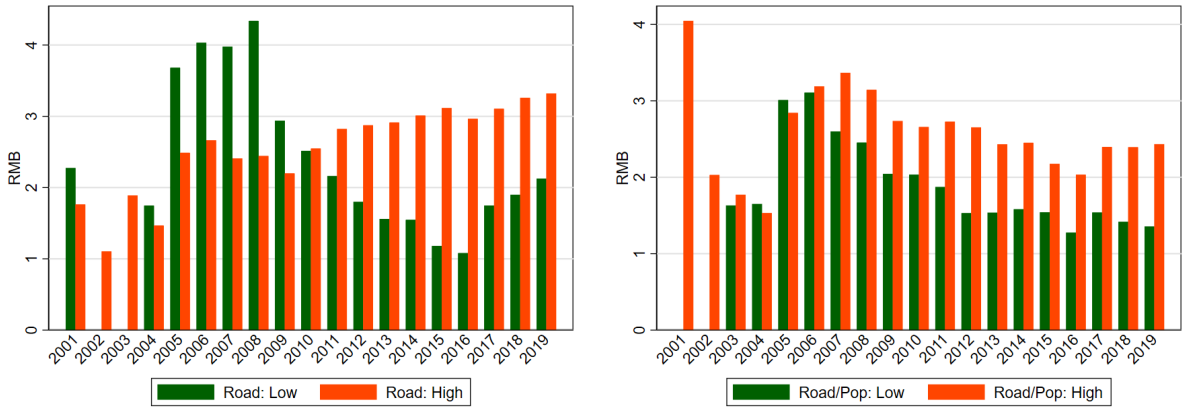
Note: The figure plots the annual local government spending multiplier for coastal and inland provinces separately, i.e., the increase of real GDP in that year for a one RMB increase of net accumulative government spending calculated at the annual depreciation rate of 5%.

The initial road conditions. During 2001-2019, about 60%-80% of local government infrastructure spending is on the transportation facilities. If the transportation investment features decreasing return to scale for this period, we would expect smaller multiplier for cities that start with better transportation facilities. To check if this prediction is true, I divide the cities into two groups based on the central sub-city's total road area and road area per capita in 2000.[12] I then repeat the two-step estimation procedures and report the annual multiplier for the two groups separately.

As shown in Figure 13, regardless of grouping based on total road area or road area per capita, the magnitude of the multipliers does not seem to depend on the initial road conditions.

[12]I do not group cities based on the city-level road area because the data is at the sub-city level and only available for the large sub-cities.

However, it does not imply that the return from transportation investment can be maintained at the estimated level in the future. In 2000, all cities have much smaller road network than now, and the small difference between road conditions does not lead to meaningful difference in local government spending multiplier. Yet at the current level of transportation networks, the marginal return from additional investment may be quite different.



(a) Road area in 2000

(b) Road area per capita in 2000

Figure 13: Local govt spending multiplier and initial road coverage

Note: The figure plots the annual local government spending multiplier for cities with different level of initial road coverage. The multiplier is the increase of real GDP in that year for a one RMB increase of net accumulative government spending calculated at the annual depreciation rate of 5%. The first graph groups cities by the central sub-city's total road area in 2000; the second graph groups cities by the central sub-city's road per capita in 2000.

Final discussion. As highlighted by Ramey (2011a), the magnitude of the multiplier depends on the characteristics of fiscal experiments. I discuss several important features of the fiscal experiment in this paper. The first is related to the finance of the fiscal spending. Unlike other experiments where the local government spending is financed by taxes or federal spending, the marginal change of local government spending in this paper is financed by less transfers to occupants removed from the land. Conceptually, this works like a non-distortive lump-sum tax on local residents. In later years when the economy grows, the local government's tax revenues increase. But in other papers, the multiplier is usually so small to generate sizable impact on the local government tax revenues.

Second, I have examined a persistent rather than temporary shock to local government spending. A persistent change of government spending usually leads to higher multipliers than a temporary change.

Lastly, one may be concerned that the estimates in this paper may suffer from anticipation bias. As argued by Ramey (2011b), when the market participants anticipate the future increase of government spending, they may respond before the spending actually happens. In my context, as firms may take into account of future government spending when deciding which city to enter, if raw is positively correlated with future government spending, then the estimated effect of accumulative government spending on current GDP will be biased upwards. This concern is likely to valid before 2012. But after 2012, as I show in Figure 5, raw is not significantly correlated with the flow of government spending after 2012 thanks to central government transfers and local government issuance of debt, the estimated M_t after 2012 is likely immune to this bias.

5 Spillover Effect

A central topic in the estimation of local government spending is the geographic spillovers. In Table (4), I do not find any evidence supporting spillovers across cities. Within each city, different sub-cities are more integrated and there could be spillover effects across different sub-cities. Such spillovers are not likely to be driven by the reallocation of funding among these sub-city governments because they are independent in finance. The existence of the spillovers can only be caused by the interaction of market participants.

I will start with an econometric model to decompose the effect of raw into the direct effect of the sub-city's spending on itself and the spillover effect on other sub-cities within the city. I will then estimate the model and evaluate the relative magnitude of the direct and spillover effect.

5.1 Econometric Model

Recall the reduced form regression model describing the effect of raw_c on $\log(GDP_{c,t})$:

$$\log(GDP_{c,t}) = \Theta_t \cdot raw_c + \alpha_c + \gamma_{p(c),t} + \varepsilon_{c,t} \tag{15}$$

In Eq. (15), c denotes city, t denotes year, and $p(c)$ is the province of city c. I model $\log(GDP_{c,t})$ as consists of a dynamic treatment effect of its raw_c, $\Theta_t \cdot raw_c$, a city fixed effect of α_c, a province-by-year fixed effect $\gamma_{p(c),t}$, and a random shock term $\varepsilon_{c,t}$. The parameter Θ_t captures the city-wide general equilibrium effect. It means when the city-wide raw land proportion increases by one percent, how much the total GDP would increase. Under the assumption that the treatment effect is homogeneous across different sub-cities, Θ_t also reports the GDP growth of each sub-city when the city-wide raw land proportion increases.

Now, consider a similar specification on the sub-city level:

$$\log(GDP_{c,i,t}) = \hat{\theta}_t \cdot raw_{c,i} + \alpha_{c,i} + \gamma_{p(c),t} + \varepsilon_{c,i,t} \tag{16}$$

In Eq. (16), i denotes the sub-city in city c, and $\hat{\theta}_t$ decribes when the sub-city's own raw land proportion, $raw_{c,i}$, increases by one percent, how much its own GDP would increase. For sub-cities in the same city, $raw_{c,i}$ and $raw_{c,i'}$ are likely to be positively correlated, $Cov(raw_c, raw_{c,i}) > 0$. If $raw_c = raw_{c,i}$, then $\hat{\theta}_t = \Theta_t$; if $raw_c \neq raw_{c,i}$, then increase of $raw_{c,i}$ is not accompanied with the same increase of $raw_{c,i'}$ of other sub-cities in the same city, and hence $\hat{\theta}_t \neq \Theta_t$ in case of either negative or positive spillover effect across different sub-cities.

To capture such spillover effect, I augment Eq. (16) by adding the term, $spillover_{c,i} \equiv raw_c - raw_{c,i}$:

$$\log(GDP_{c,i,t}) = \theta_t \cdot raw_{c,i} + \beta_t \cdot spillover_{c,i} + \alpha_{c,i} + \gamma_{p(c),t} + \varepsilon_{c,i,t} \tag{17}$$

In Eq. (17), holding $spillover_{c,i}$ fixed, θ_t describes when both sub-city i and all other sub-cities in the same city increase their raw land proportion by one percent, how much the sub-city i's GDP would increase; conceptually, $\theta_t = \Theta_t$. Holding $raw_{c,i}$ constant, β_t captures the marginal spillover effect of raw_c due to the change of raw land proportion in other sub-cities in the same city.

Proposition 1. *Assume Eq. (17) is the underlying data generating process for* $\log(GDP_{c,i,t})$. *If* $\varepsilon_{c,i,t} \perp raw_{c,i',t}$ *and* $GDP_{c,i,0} \propto DownTown_{c,i}$, *then the city-wide causal effect of* raw_c *on* $\log(GDP_{c,t})$ *is approximately* θ_t, *i.e.*, $\Theta_t \approx \theta_t$.

Of course, one can direct estimate Eq. (15) to get Θ_t. The advantage of estimating Eq.

(17) is that we can separately estimate the general equilibrium effect and the spillover effect. Instead of regression on $(raw_{c,i,t}, spillover_{c,i,t})$, one may also regress on $(raw_{c,i,t}, raw_{c,t})$, but the coefficient will not be straightforward to interpret. The coefficient loading on $raw_{c,i,t}$ would be the effect when the proportion of raw land increases in the sub-city but decreases in other sub-cities such that the city-wide raw land proportion remains unchanged.

What if θ_t is heterogeneous? Denote the effect for sub-city i as $\theta_{i,t}$. The estimation of Eq. (17) will deliver the average effect, $\mathbf{E}[\theta_{i,t}]$. The estimation of Eq. (15) will deliver the weighted average effect,

$$\Theta_t = \mathbf{E}\left[\frac{DownTown_{c,i}}{DownTown_c} \cdot \theta_{i,t}\right].$$

As long as $\theta_{i,t}$ is not correlated with the relative size of the sub-city, we will still have $\theta_t = \Theta_t$. As we will see below, indeed the two estimates, $\hat{\theta}_t$ and $\hat{\Theta}_t$, are very close in terms of magnitude.

Finally, let us decompose the total effect into the direct effect and spillover effect. Consider a marginal increase of $raw_{c,i}$ by μ; as a result, raw_c will increase by $\frac{DownTown_{c,i}}{DownTown_c}\mu$. By Eq. (22), $GDP_{c,i,t}$ will increase by

$$\Delta GDP_{c,i,t} = GDP_{c,i,0} \cdot \bar{y}_{p(c),t} \cdot (\theta_t - \beta_t(1 - \frac{DownTown_{c,i}}{DownTown_c}))\mu,$$

and $GDP_{c,i',t}$ $(i' \neq i)$ will increase by

$$\Delta GDP_{c,i',t} = GDP_{c,i',0} \cdot \bar{y}_{p(c),t} \cdot \beta_t \frac{DownTown_{c,i}}{DownTown_c}\mu.$$

The total spillover effect to all other sub-cities sums up to

$$\sum_{i' \neq i} \Delta GDP_{c,i',t} = (GDP_{c,0} - GDP_{c,i,0}) \cdot \bar{y}_{p(c),t} \cdot \beta_t \frac{DownTown_{c,i}}{DownTown_c}\mu.$$

Now, let all sub-cities in city c increase their raw land proportion by μ. The total direct effect sums up to

$$\sum_i \Delta GDP_{c,i,t} = \Big(\theta_t \cdot GDP_{c,0} - \beta_t \cdot \sum_i GDP_{c,i,0}(1 - \frac{GDP_{c,i,0}}{GDP_{c,0}})\Big)\bar{y}_{p(c),t}\mu.$$

The total spillover effect sums up to

$$\sum_{i}\sum_{i'\neq i}\Delta GDP_{c,i',t} = \beta_t \cdot \sum_{i} GDP_{c,i,0}(1-\frac{GDP_{c,i,0}}{GDP_{c,0}})\bar{y}_{p(c),t}\mu.$$

The total effect is hence

$$\sum_{i}\Delta GDP_{c,i,t} + \sum_{i}\sum_{i'\neq i}\Delta GDP_{c,i',t} = \theta_t \cdot GDP_{c,0}\bar{y}_{p(c),t}\mu.$$

5.2 Heterogeneity with Population Density

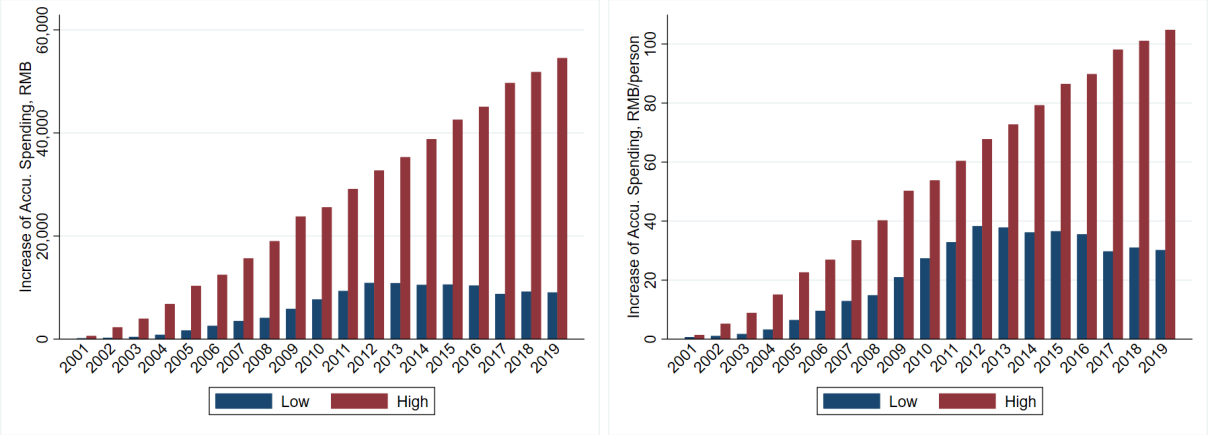
The existence and the magnitude of the geographic spillovers are likely to depend on the scale of local government spending. As raw shifts the local government spending by saving the government the compensation cost to occupants, a 1% change of raw will generate a larger impact if the compensation rate per square meter of land is higher. The compensation rate itself highly depends on the sub-city's land price.

In the data, a stronger predictor for the future land price is the population density in 2000. In Appendix Table (A.4), I show that higher population density is strongly positively correlated with land supply and land price, and the correlation is robust to the inclusion of the estimated downtown size and GDP per capita in 2000. The GDP per capita in 2000 is significantly correlated with the equilibrium land supply, but not with the average equilibrium land price.

Due to the large heterogeneity across population density, I will allow the spillovers to differ with respect to the population density. Appendix Figure A.3 plots the population density of the satellite sub-cities and the central sub-cities. The central sub-city is defined as the one with the largest GDP in 2000 among all the sub-cities within each city. I will group all cities and sub-cities based on the population density of the central sub-city for three reasons. First, there is not much variation of population density among different satellite sub-cities. Almost all the satellite sub-cities have a population density below 0.1. The population density of the central sub-city, however, is very disperse and ranges between 0 and 0.8. Second, the central sub-city likely plays a more important role in generating the spillovers than any other sub-cities. On average, the central sub-city accounts for about half of the total GDP of the city. Third, as I will compare the effect on the sub-city and city level, it is easier to have all sub-cities to be in the same group

as the city. Dividing sub-cities based on their own population density would lead to inconsistency between the grouping of sub-cities and cities.

To have some sense of how much the effect of raw on local government spending depends on the initial population density, I calculate the estimated increase of local government spending for a 1% increase of raw_c for cities with high and low population density separately, using Equation (8) and (9). As shown in Figure 14, the result is much larger for cities with higher population density, regardless whether we scale the effect by population or not.



(a) Accumulative Spending

(b) Accumulative Spending per capita

Figure 14: Marginal effect on accumulative govt spending of raw

Note: The figures plot the average marginal increase of the accumulative govt spending, both total and per capita, for a 1% increase in raw. I group cities based on the central sub-city's population density in 2000 and conduct the estimation separately.

5.3 Empirical Results

I now conduct the estimation using Equation (17) for the two groups of sub-cities divided based on the central sub-city's population density in 2000. Table 5 shows the estimation results.

In Panel A, without controlling for the spillover effect term, the estimated coefficient of raw is significant and positive for both central and satellite sub-cities. When the spillover term $spillover$ is included, the estimated coefficient of raw for the central sub-city barely changes and the $spillover$ is insignificant, indicating that there is little spillover effect

from the satellite sub-cities to the central sub-city. For the satellite sub-cities, the estimated coefficient on raw almost doubles with the inclusion of $spillover$, and the coefficient estimate of $spillover$ is also positive and significant. This suggests positive spillover effects from other sub-cities to the satellite sub-city.

In Panel B, we repeat the same estimation for the group of sub-cities with low population density. In contrast to Panel A, there is no significant evidence supporting any spillover effect across different sub-cities. This is consistent with the fact that raw induces a much smaller increase of government spending for cities with lower population density, as shown in Figure 14.

I now decompose the total effect into direct and spillover effect for the group of cities with high population density, using the framework from Section (5.1). Figure 15 shows the direct and spillover effect for a 1% increase in raw for each year. The magnitudes of the direct and spillover effect are on the same scale. On average, 45% of the total effect is direct effect and 55% is the spillover effect. As comparison, if the effect of the sub-city i's spending is evenly distributed among all sub-cities within the city, then the ratio between direct and total effect would be the 1 to the average number of sub-cities within each city, which is about 1/6-1/7.

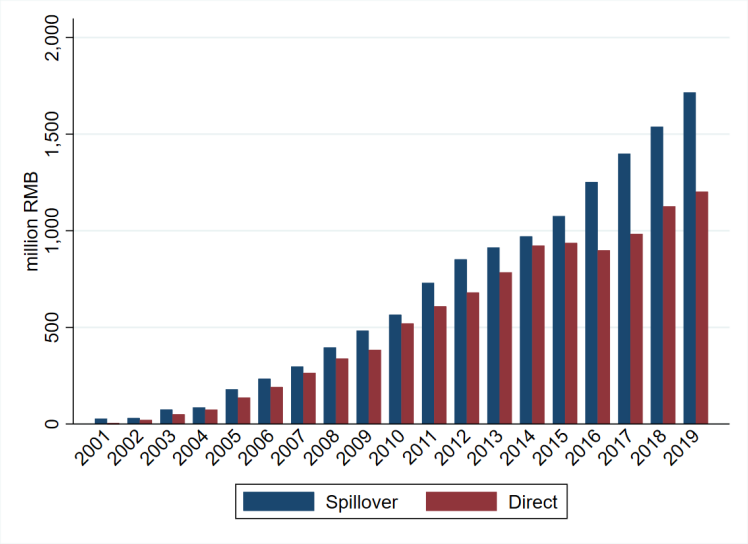


Figure 15: Decomposition of GDP Effect for 1% Increase of raw

Note: The graph shows the average direct and spillover effect on GDP when $raw_{c,i}$ increases by 1%.

The large spillover effect can shed light on coordination between neighboring sub-

Table 5: Spillover effect on GDP within the city

Panel A: Pop Density: High

	(1)	(2)	(3)	(4)	(5)	(6)
Sub-city	All	Central	Satellite	All	Central	Satellite
Dep Var	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
$\mathbb{1}_{t>2000} \cdot raw$	0.212***	0.577***	0.215***	0.472***	0.594***	0.459***
	(3.432)	(5.150)	(3.453)	(4.785)	(4.135)	(3.922)
$\mathbb{1}_{t>2000} \cdot spillover$				0.450***	0.0696	0.396***
				(3.647)	(0.221)	(2.939)
Sub-city FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Base Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,755	3,585	20,979	24,755	3,585	20,979
R-squared	0.982	0.985	0.978	0.982	0.985	0.979
Within R-sq.	0.0301	0.0727	0.0553	0.0386	0.0728	0.0622
#City	159	150	154	159	150	154

Panel B: Pop Density: Low

	(1)	(2)	(3)	(4)	(5)	(6)
Sub-city	All	Central	Satellite	All	Central	Satellite
Dep Var	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
$\mathbb{1}_{t>2000} \cdot raw$	0.165**	0.136	0.161**	0.192	0.120	0.187
	(2.483)	(0.760)	(2.332)	(1.650)	(0.550)	(1.591)
$\mathbb{1}_{t>2000} \cdot spillover$				0.0422	-0.0490	0.0390
				(0.341)	(-0.152)	(0.317)
Sub-city FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Base Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,476	3,642	22,783	26,476	3,642	22,783
R-squared	0.981	0.978	0.979	0.981	0.978	0.979
Within R-sq.	0.0382	0.0217	0.0425	0.0383	0.0217	0.0426
#City	176	155	169	176	155	169

Note: These two tables report estimation results about the within-city spillover effect on GDP using Eq. (17). I divide the sub-cities into two groups based on the central sub-city's population density in 2000. Standard errors are clustered by cities. T-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cities. In the context of China, local officials are evaluated and promoted based on the local economic performance. If such evaluation is based on the relative performance as compared to that in the neighboring sub-cities, it will affect the local officials' incentive to spend and to promote economic growth because they are negatively impacted by the positive spillovers of their spending on their competitors. Such coordination problem is mitigated if they are evaluated based on the absolute growth from previous years or based on comparison with sub-cities in other cities.

6 Mechanisms

In this section I will provide evidence showing that the mechanism is consistent with the model where the government spending is investment rather than consumption. In particular, I will test the opposite predictions on the response of the labor market by the two different models. I will then provide direct evidence showing that government spending increases firms' productivity and access to the input and output market, and these benefits leads to crowd-in of private investment in the form of more firm entry, which can explain the persistence of the effect of local government spending.

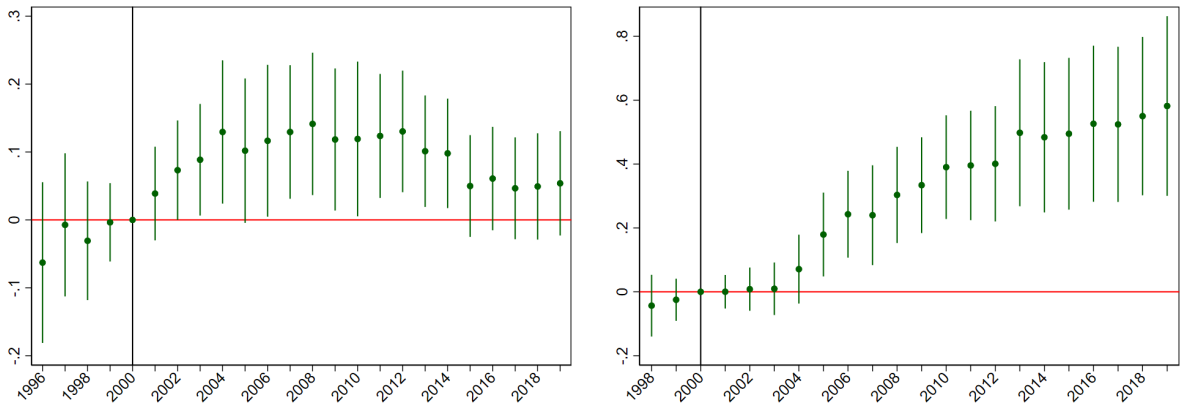
6.1 The Response of Labor Market

Government consumption and investment consumption have different predictions on the response of the labor market (Ramey et al., 2020). As I discuss above, in the neoclassic approach, government consumption financed by local households decreases household wealth, and the rise of labor supply induced by the wealth effect is the key mechanism through which government consumption spending raises output. The increase of labor supply predicts the decrease of equilibrium wages. The government investment spending financed by local households leads to similar negative wealth effect; but beyond that, higher public capital increases the marginal output of labor and hence labor demand in the future, which mitigates or even changes the sign of the negative wealth effect of increased government spending, depending on the marginal productivity of government investment. As a result, the smaller increase of labor supply due to less negative wealth effect and the increase of labor demand will lead to less negative or positive effect on equilibrium wages. In other words, the rise of wages can only be consistent with the

model of government investment spending, rather than consumption spending.

In this paper, the change of government spending driven by raw is financed by local households, as higher raw implies less transfer payments to the occupants removed from their land. Conceptually, it works similarly to a lump-sum tax. Papers on the local government spending also finds positive employment effect (Dupor and McCrory (2018)), but in their setting the local government spending is financed by federal grants rather than local households, which imposes no negative wealth effect on local residents.

Figure 16 shows the estimated treatment effect of raw on the city's employment and wages after 2000, using Equation (5). Cities with differential raw were on the parallel trends before 2000 in terms of both average wage and employment. After 2000, higher raw leads to an increase of both employment and wages, which suggests the shift of labor demand curve rather than the labor supply curve. Over time, when workers move across different cities, the effect on employment continues to grow and the gap of wages starts to close. The evidence suggests that the mechanism is only consistent with the model where government spending is investment rather than consumption.



(a) $\log(Wage_{c,t})$ (b) $\log(Emp_{c,t})$

Figure 16: Marginal Effect of raw on Equilibrium Wage and Employment

Note: The figure plots the 95% confidence interval of the β estimates from Equation (5), where the dependent variable is indicated below each graph. Note for employment, the data is only available for 13 cities before 1998 and so I start from 1998. All standard errors are clustered by the city.

6.2 Extensive Margin: Firm Entry

Let us first look the effect on firm entry. Using the firm registry information data, I calculate $\#Mfr_{c,i,t}$, the number of manufacturing firms that are registered in sub-city i of city c and have established but not exited yet in the beginning of year t. The sample goes from 1996 to 2017. I then use $\log(\#Mfr_{c,i,t})$ as the dependent variable and estimate Equation (17).

Table 6 reports the results. As in studying the spillover effect on GDP, I divide firms into two groups based on the population density of their registered city. In cities with high population density, there is significant and positive effect of raw on the number of manufacturing firms, and the effect holds for both central and satellite sub-cities. The magnitude is economically important. A 1% increase in raw leads to an increase of the number of manufacturing firms by about 0.52%. The magnitude is close to what I find in Table 5 Panel A, where a 1% increase in raw leads to a growth of real GDP by about 0.47%. Therefore, the large multipliers found in this paper can be explained by the fact that local government spending has led to more firm entry. Moreover, after entry, firms will continue to produce output each year, which also explains why the multiplier has been quite persistent over time.

In cities with low population density, however, the effect on the number of manufacturing firms is still positive but insignificant and smaller in magnitude. The estimated coefficient is close to what is found for GDP in Table 5 Panel B.

6.3 Intensive Margin: Productivity and Output Demand

So far, I have shown that local government spending has generated large multipliers, the magnitude of which can be explained by the effect on firm entry. The next question is, how does government spending lead to such an increase of firm entry in the first place? I answer this question by studying the effect of local government spending, proxied by raw, on individual firms' production and output.

Table 6: Government spending and the number of manufacturers

	(1)	(2)	(3)	(4)	(5)	(6)
Pop. Density	High	High	High	Low	Low	Low
Sub-city	All	Central	Satellite	All	Central	Satellite
Dep Var	log(#Mfr)	log(#Mfr)	log(#Mfr)	log(#Mfr)	log(#Mfr)	log(#Mfr)
$\mathbb{1}_{t>2000} \cdot raw$	0.521**	0.914***	0.461*	0.255	0.0118	0.254
	(2.154)	(3.211)	(1.750)	(1.302)	(0.0318)	(1.346)
$\mathbb{1}_{t>2000} \cdot spillover$	0.534**	1.281**	0.492*	0.0537	-0.925	0.107
	(2.121)	(2.198)	(1.822)	(0.269)	(-1.043)	(0.575)
Base Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,378	3,300	19,880	24,327	3,396	20,887
R-squared	0.966	0.966	0.960	0.960	0.973	0.956
#City	160	150	156	175	155	167

Note: This table shows both the direct and spillover effect of sub-city government spending on the number of manufacturers and how the effect depends on the scale of the spending proxied by the central sub-city's population density in 2000. All standard errors are clustered by city. T-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3.1 Local firms' output and decomposition.

Assume the following production function for firms:

$$Q_{k,j,t} = A_{k,j,t} \cdot (Z_{k,j,t}K_{k,j,t})^{\alpha_k^j} \cdot (C_{k,j,t}L_{k,j,t})^{\alpha_l^j} \cdot M_{k,j,t}^{\alpha_m^j} \tag{18}$$

In Equation (18), $Q_{k,j,t}$ is the output of firm k from industry j in year t, measured by the price in 1990; $A_{k,j,t}$ is the measure of productivity, $Z_{k,j,t}K_{k,j,t}$ is effective utilization of capital $K_{k,j,t}$, $C_{k,j,t}L_{i,t}$ is effective utilization of labor $L_{k,j,t}$, and $M_{k,j,t}$ is material. Unlike a technology shock that directly affects firms' technology, local government spending may work by increasing access to larger markets, which will lead to direct impact on the firms' resource utilization. Including utilization in the residual productivity measure may affect the interpretation about the effect on productivity.

By taking logarithm, we can decompose the real output into five components:

$$\log(Q_{k,j,t}) = tfpq_{k,j,t} + utili_{k,j,t} + \alpha_m^j \cdot \log(M_{k,j,t}) + \alpha_k^j \cdot \log(K_{k,j,t}) + \alpha_l^j \cdot \log(L_{k,j,t}), \tag{19}$$

where $tfpq_{k,j,t} = \log(A_{k,j,t})$ and $utili_{k,j,t} = \alpha_k^j \log(Z_{k,j,t}) + \alpha_l^j \log(M_{k,j,t})$.

There are many ways to obtain the factor share $(\alpha_k^j, \alpha_l^j, \alpha_m^j)$ and the TFPQ measure, a subject of ongoing debt in the literature. I will estimate the production function with the simple "factor share" method (Criscuolo et al., 2019). Appendix **??** provides details on the construction of factor share and firms' TFPQ.

To measure utilization, I follow Basu (1996) and estimate utilization as follows:

$$utilization_{k,j,t} = \alpha_k^j \cdot (\log(M_{k,j,t}) - \log(K_{k,j,t})) + \alpha_l^j \cdot (\log(M_{k,j,t}) - \log(L_{k,j,t}))$$

The $tfpq_{k,j,t}$ is then defined as the residual by subtracting the other four components from $\log(Q_{k,j,t})$.

With the measure of the five components, I then examine the effect of raw with the following specification:

$$y_{k,j,t} = \theta raw_{c,i(k)} + \beta spillover_{c,i(k)} + \gamma_{p(k),j,t} + \varepsilon_{k,j,t}, \tag{20}$$

where $y_{k,j,k}$ is one of the six variables in Equation (19), $raw_{c,i(k)}$ is the raw of the sub-city where the firm k is registered, $spillover_{c,i(k)}$ is the spillover effect on the sub-city, $\gamma_{p(k),j,t}$ controls for province-industry-year fixed effect, and $\varepsilon_{k,j,t}$ is the residual term.[13]

Table 7 reports the estimation results using firms registered in cities with high population density in 2000 with the sample period of 2001-2007. In Column (1), there is a significant and positive effect of raw on the firm's real output. The magnitude of the effect is economically important. A 1% increase inf raw leads to the growth of firms' output by 0.32%. In Column (2)-(6), I decompose the effect into five different components. Roughly half of the effect is driven by an increase of material uses, 1/4 by an increase of productivity, and 1/4 by more efficient resource utilization.

6.3.2 Heterogeneity with transportation uses.

If the local government spending increases output by increasing demand, we may also find the same sign of the effect as in Table 7, although the magnitude of the effect may not be that large. One additional test to support the argument that government spending increases firms' access to bigger markets is the heterogeneity with respect to the use of

[13]The industry classification is taken from China Input-Output Table of 2002. In the Annual Survey of Industrial Firms, firms are classified based on China's Industrial Classification for National Economic Activities 1994 and 2002. I match the classification with the that used in China Input-Output Table of 2002.

Table 7: Government spending and local firms' output

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	log(Q)	tfpq	utili	$s^m \cdot \log(M)$	$s^k \cdot \log(K)$	$s^l \cdot \log(L)$
raw	0.321**	0.0838***	0.0781**	0.169*	-0.00724	-0.00478
	(2.371)	(2.656)	(2.350)	(1.801)	(-0.254)	(-0.981)
spillover	0.373**	0.0952***	0.0864**	0.187*	-0.00845	0.00464
	(2.584)	(2.727)	(2.070)	(1.768)	(-0.247)	(0.815)
Prov-Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	889,993	882,901	887,330	892,679	895,264	900,829
R-squared	0.182	0.365	0.194	0.267	0.602	0.764
#City	160	160	160	160	160	160

Note: This table shows in cities where the central sub-city's population density is high, the direct and spillover effect of sub-city government spending on local firm's output. Column (2)-(6) decompose the effect on output into productivity, utilization, and input uses. The sample includes all firms during 2001-2007. All standard errors are clustered by city. T-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Government spending and firms' use of transportation services

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	log(Q)	tfpq	utili	$s^m \cdot \log(M)$	$s^k \cdot \log(K)$	$s^l \cdot \log(L)$
Low*raw	0.265**	0.0680**	0.0882***	0.139	-0.0244	-0.0102
	(2.147)	(2.194)	(2.660)	(1.599)	(-0.765)	(-1.546)
Low*spillover	0.297**	0.0685**	0.0938**	0.154	-0.0232	-0.00413
	(2.062)	(1.984)	(2.162)	(1.431)	(-0.610)	(-0.561)
High*raw	0.380**	0.101***	0.0676*	0.201*	0.0109	0.00113
	(2.253)	(2.665)	(1.844)	(1.718)	(0.377)	(0.231)
High*spillover	0.456***	0.123***	0.0792*	0.224*	0.00738	0.0141**
	(2.614)	(2.886)	(1.772)	(1.799)	(0.207)	(2.352)
Prov-Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	882,308	875,304	879,699	884,979	887,574	893,080
R-squared	0.181	0.365	0.194	0.266	0.602	0.764
#City	160	160	160	160	160	160

Note: This table shows in cities where the central sub-city's population density is high, how the direct and spillover effect of sub-city government spending on local firm's output depends on the firms' dependence on transportation services, i.e., the share of transportation service expenses in total intermediate input expenses. The sample includes all firms during 2001-2007. All standard errors are clustered by city. T-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

transportation services.

Fernald (1999) shows that when growth in roads changes, productivity growth changes disproportionately in U.S. industries with more vehicles, an proxy for the use of transportation services. I do not have data on the firm's vehicles. Instead, I directly measure the industry's uses of transportation services using China's Input-Output table of 2002. For each output industry, I calculate the share of railway, highway, waterway and urban public transportation services in the industry's total intermediary output. I then generate a binary indicators of low, which equals 1 if the firm is in an industry with transportation cost share below the median and 0 otherwise. I then define $high = 1 - low$, and interact $(raw, spillover)$ with $(low, high)$ in Equation (20).

Table 8 reports the results. In Column (1), as predicted, the effect of raw and $spillover$ is about 50% larger for firms with more uses of transportation services than for firms with less uses of transportation services. There is a similar magnitude of difference in terms of productivity in Column (2). In Column (3), the two groups of firms do not differ in terms of the response of utilization. But in Column (4), the effect on material uses is only significant for firms with more uses of transportation services. In Column (5) and (6), although insignificant, the effect on capital and labor uses is negative for firms with less uses of transportation but positive for firms with higher uses of transportation.

To sum, the heterogeneity with respect to the use of transportation services is consistent with the conjecture that government spending increases firms' access to bigger markets.

6.3.3 Supply chain and spillovers.

In the last section, I provide firm-level evidence on the spillover effect across sub-cities. Due to fiscal independence of different sub-cities, it is not likely that the spillover effect is due to transfer of funds across different sub-city governments. Below I will provide evidence of the spillover effect through the spread of technology and output-input linkages.

First, the spread of technology is stronger if two firms are in the same industry and share similar technology. To test this prediction, I construct a horizontal exposure measure based on the similarity between the firm's own industry and the industry of firms in

Table 9: Government spending and firms' supply chain position

Panel A: Horizontal Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Horizontal Exposure	High	Low	High	Low	High	Low
Dep Var	log(Q)	log(Q)	tfpq	tfpq	log(Q)	log(Q)
raw	0.316***	0.385***	0.110***	0.0433	0.266**	0.372***
	(2.908)	(3.015)	(2.942)	(1.342)	(2.538)	(2.958)
spillover	0.317**	0.424***	0.174***	0.0609	0.254*	0.408***
	(2.336)	(2.712)	(3.708)	(1.647)	(1.865)	(2.640)
tfpq					0.386***	0.377***
					(8.100)	(9.569)
Prov-Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,076	111,437	134,604	110,184	134,604	110,184
R-squared	0.184	0.218	0.292	0.292	0.194	0.226
#City	156	160	156	160	156	160

Panel B: Vertical Exposure

	(1)	(2)	(3)	(4)
Downstream Exposure	High	High	Low	Low
Upstream Exposure	High	Low	High	Low
Dep Var	log(Q)	log(Q)	log(Q)	log(Q)
raw	0.622***	0.389***	0.328*	0.247*
	(3.758)	(3.296)	(1.916)	(1.708)
spillover	0.502**	0.359**	0.352*	0.283
	(2.162)	(2.062)	(1.960)	(1.558)
Prov-Ind-Year FE	Yes	Yes	Yes	Yes
Observations	40,411	66,516	67,216	72,314
R-squared	0.296	0.189	0.191	0.160
#City	160	155	156	155

Note: These tables show how the effect of government spending on local firms depend on the firms' relative supply chain position. Panel A groups local firms based on the horizontal exposure, i.e., the presence of competing firms in the same industry in other sub-cities within the same city; Panel B groups local firms based on the vertical exposure, i.e., the probability of selling and buying from firms in other sub-cities within the same city. The sample includes all firms during 2001-2003. All standard errors are clustered by city. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

other sub-cities of the same city. Specifically,

$$Horizontal_{c,i,j} = \frac{\sum_{k:c(k)=c,i(k)\neq i} Sale_{k,j,2000}}{\sum_{k:p(k)=p(c)} Sale_{k,j,2000}} \tag{21}$$

In words, $Horizontal_{c,i,j}$ is the share of sales from firms in city c but not sub-city i in the total sales of firms in the same province as city c for industry j in year 2000. I use the industry composition information in 2000 to avoid endogenous change of industries after 2000. The denominator is to control for different size of industries. Intuitively, a higher value of $Horizontal$ implies more firms from the same industry are located in the other sub-cities. For each sub-city i, I then divide the industries j into two equal groups based on $Horizontal_{c,i,j}$. The within-sub-city classification ensures that raw and $spillover$ are comparable for the two groups.

Table 9 Panel A shows how the spillover effect depends on the extent of horizontal exposure. In Column (1) and (2), the effect on firms' output is similar for the two groups. In Column (3) and (4), as predicted, the spillover effect on $tfpq$ is only significant and positive for firms with high horizontal exposure. In Column (5) and (6), after controlling for $tfpq$, the effect on firms' output is smaller for firms with high horizontal exposure, as high horizontal exposure implies more competition. To summarize, higher horizontal exposure leads to greater spillover effect on technology since firms would share more similar technology, but smaller effect on output after controlling for productivity due to more competition.

Second, the spillover through output-input linkage is stronger if firms are more vertically connected to firms from other sub-cities. To test this prediction, I construct two measures of vertical exposure. The upstream exposure measures the probability that a firm in city c and sub-city i buys inputs from firms in other sub-cities in city c. The downstream exposure measures the probability that a firm in city c and sub-city i sells output to firms in other sub-cities in city c. Appendix E provides details on the calculation of the two measures. For each sub-city i, I then divide the industries j into two equal groups based on $Downstream$ exposure and $upstream$ exposure separately.

Table 9 Panel B shows how the effect on firms' output depends on the firms supply chain position. As predicted, the spillover effect is highest for firms with both high downstream and high upstream exposure; the magnitude decreases to about half for the group of high downstream and low upstream or high upstream and low downstream

exposure; it is smallest for the group with both low downstream and low upstream exposure.

To summarize, the spillover effect depends on the firms' supply chain position. The technology spread is higher if firms share similar technology to firms in other sub-cities; the spillover effect through output-input linkages is stronger if firms are more connected with firms in other sub-cities, either in terms of upstream or downstream.

7 Conclusion

The size of the government spending multiplier can help justify the size of the government. Despite the well-recognized incentive schemes of local officials to promote economy growth, there has been widespread suspicion on China's government deep involvement with the market economy (Alder et al., 2021), a question that cannot be answered without a good sense of the return of the government spending. The estimation of fiscal multiplier is complicated with big governments as they depend on the nature of the local policies, i.e., how the money is spent.

The paper makes several contributions towards the understanding of the effect of local government spending in developing countries like China. First, I develop an innovative identification strategy by exploring the local government's endowment of free raw land. Second, the government spending multiplier can be large if it is spent in a productive way, for example, by increasing the local firms' access to bigger markets and their productivity. Third, there will be positive spillover effects, and policies should be designed to avoid coordination failture among different governments.

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Online Appendix

A Supplementary material for Section 2

Table A.1: Data Summary

Panel A: City level data

Obs	Variables	Definition
City	raw	Raw Land Proportion at the end of 2000.
	InfraInvt2Sale	Urban Infrastructure investment financed by land sales/total land sales during 2001-2005.
	landexp2supply	Urban land expropriated during 2001-2013/Land supplied during 2003-2015.
	logdebt2budg	Log (Municipal debt balance in 2017/Budgetary Revenue in 2008).
	CitySpillover	Inverse distance-weighted average raw of other cities, where distance is between the centroid of central sub-cities.
	Cyclicality	OLS coefficient by regressing the city's annual real GDP growth rate on the country's annual real GDP growth rate during 1996-2000.
City-Year	GDP	GDP in 100 million RMB.
	GDP_sec	GDP in the secondary sector in 100 million RMB.
	GDP_ter	GDP in the tertiary sector in 100 million RMB.
	GDP_nr	GDP minus real estate invest in 100 million RMB.
	Emp	Total number of employees in the non-aggriculture sector, 10,000 person.
	Wage	Average wage of employees in the non-agriculture sector, RMB per year.
	POP	population in 10,000 people.
	#Mfr	the number of manufacturers at the beginning of the year.
	LandSupply	Annual land supply via agreement, bidding, auctions and listing, hectare. Before 2016, the data is from China Land and Resources Statistical Yearbook; after 2016, it is by summing transaction-level data from the Ministry of Natural Resources after 2016.
	LandExp	Annual land expropriated with compensation, hectare. Data is by summing the value at the sub-city level from the Urban Construction Statistic Yearbook.
	NetLandSupply	(LandSupply - LandExp) / estimated downtown area, trimmed at the 1st and 99th percentile.
	BudExp	City government budgetary expense, 100m RMB.
	BudRev	City government budgetary revenue, 100m RMB.

Panel B: Sub-city level data

Obs	Variables	Definition
Subcity	RawProp	Raw Land Proportion at the end of 2000.
	popden	Total population / urban land size in 2000, person/100 Sq.Me.
Subcity-Year	GDP	GDP in 100 million RMB.
	POP	Population in 10,000 people.
	InfraInvest	Total facility invest in 10,000 RMB.
	TranspInvest	Transporation (road plus railways) invest in 10,000 RMB.
	Road	Road area in 10,000 Sq.Me.
	WaterPipe	Length of water pipelines in 1km.
	DrainPipe	Length of drainage pipelines in 1km.
	#Mfr	Number of manufactuers at the beginning of the year.
	LandSupply	Annual land supply via agreement, bidding, auctions and listing , hectare. Data is from the Ministry of Natural Resources.
	LandPrice	Average land price per square meter. Data is from land.china.
	ConsLand	Total urban construction land area, Sq.Km.
	ResLand	Residential land area, Sq.Km.
	IndLand	Industrial land area, Sq.Km.

Panel C: Firm level data

Obs	Variables	Definition
Firm-Year	Capital	Capital in 1000 RMB.
	Labor	Labor.
	Material	Material use in 1000 RMB.
	Output	Output measured in 1990 price in 1000 RMB.
	Sale	Output measured in current price in 1000 RMB.

B Supplementary material for Section 3

B.1 Patterns of raw

Figure A.1 shows the time series of raw and the cross sectional relationship between raw in 2000 and in 2015.

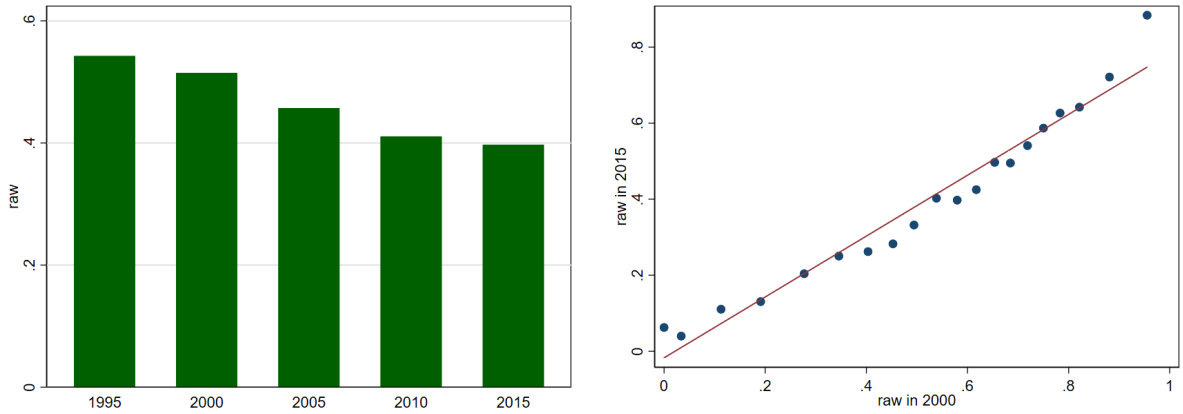

Figure A.1: Patterns of City-level raw in 2000

Note: The first graph shows the average city-level raw land proportion over time, and the second plots the binscatter of raw land proportion in 2015 against in 2000 across different cities.

B.2 Land Zoning

Figure A.2 reports the change of land zoning per capita for residential land industrial when raw increases by 1%. To check the treatment effect of raw on land zoning, I estimate Equation (6) using the log size of land zoned as residential and industrial uses as the dependent variable. With the coefficient estimates of β, I then calculate the marginal effect of a 1% increase of raw on land zoning in year t as follows:

$$\begin{aligned}\mathbf{E}\left[\Delta Y_t\right] =& \mathbf{E}\left[\exp\left(\hat{\beta}_t(raw_{c,i}+1\%)+\hat{xi}_t y_{c,i,2000}+\hat{\alpha}_{c,i}+\hat{\gamma}_{p(c),t}\right)\right] \\ &-\mathbf{E}\left[\exp\left(\hat{\beta}_t raw_{c,i}+\hat{xi}_t y_{c,i,2000}+\hat{\alpha}_{c,i}+\hat{\gamma}_{p(c),t}\right)\right]\end{aligned}$$

B.3 Substitution of Debt for Land Sale Profits

Table A.2 shows that cities with lower raw issue more debt after 2010 and have higher debt balance in 2017.

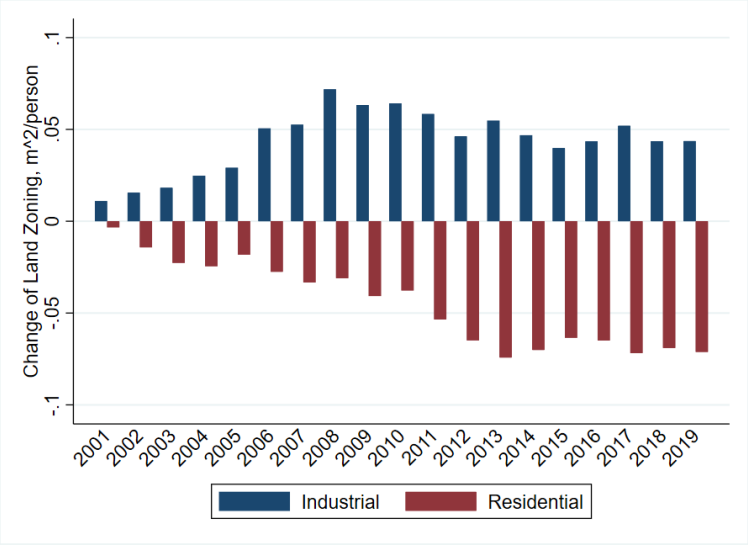

Figure A.2: The marginal effect of *raw* on land zoning

Note: These graph plots the marginal change of land zoned as industrial and residential when *raw* increases by 1%.

Table A.2: City-level *raw* and debt balance

	(1)
Year	2017
Dep Var	logdebt2budg
raw	-0.493**
	(-2.106)
Province FE	Yes
Observations	181
R-squared	0.495

Note: This table shows the correlation between the city's *raw* with its debt balance. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Supplementary material for Section 4

Table A.3 reports the Two-Stage Least Square estimation results of Equation (12).

D Supplementary material for Section 5

D.1 Proof for Proposition 1

Proof. For simplicity, I normalize the year 2000 to be $t = 0$. Without loss of generality, assume $\theta_0 = \beta_0 = 0$. Denote $\Delta\gamma_{p(c),t} = \gamma_{p(c),t} - \gamma_{p(c),0}$, $\Delta\varepsilon_{c,i,t} = \varepsilon_{c,i,t} - \varepsilon_{c,i,0}$, and $y_{c,i,t} = \frac{GDP_{c,i,t}}{GDP_{c,i,0}}$. We can then rewrite Eq. (17) as follows:

$$\log(y_{c,i,t}) = \theta_t \cdot raw_{c,i} + \beta_t \cdot spillover_{c,i} + \Delta\gamma_{p(c),t} + \Delta\varepsilon_{c,i,t} \tag{22}$$

Apply Taylor expansion of $\log(y_{c,i,t})$ at $\bar{y}_{p(c),t}$, we get

$$\log(y_{c,i,t}) \approx \frac{y_{c,i,t}}{\bar{y}_{p(c),t}} - 1 + \log \bar{y}_{p(c),t}$$

Conduct a weighted sum of Eq. (22) using $\frac{GDP_{c,i,0}}{GDP_{c,0}} = \frac{DownTown_{c,i}}{DownTown_c}$ as the weight and replacing the LHS with the Taylor expansion, we get

$$\begin{aligned}
&\frac{GDP_{c,t}/GDP_{c,0}}{\bar{y}_{p(c),t}} - 1 + \log \bar{y}_{p(c),t} \\
=&(\theta_t - \beta_t) \cdot \sum_{i:c(i)=c} \frac{DownTown_{c,i}}{DownTown_c} raw_{c,i} + \beta_t \cdot raw_c + \Delta\gamma_{p(c),t} + \Delta\varepsilon_{c,t} \\
=&\theta_t \cdot raw_c + \Delta\gamma_{p(c),t} + \Delta\varepsilon_{c,t},
\end{aligned}$$

where $\varepsilon_{c,t} = \sum_{i:c(i)=c} \frac{DownTown_{c,i}}{DownTown_c} \varepsilon_{c,i,t}$.

Reverse the Taylor expansion approximation on the LHS, we get

$$\log(GDP_{c,t}) - \log(GDP_{c,0}) \approx \theta_t \cdot raw_c + \Delta\gamma_{p(c),t} + \Delta\varepsilon_{c,t}$$

Denote $\log Y_{c,0} = \alpha_c$. We get the expression as Eq. (15).

Table A.3: The Two-Stage Least Square Estimation results

	(1)	(2)	(3)	(4)	(5)	(6)
Year	2001	2002	2003	2004	2005	2006
$\log(AG)$	0.422	0.248	0.474	0.619**	1.337***	1.559***
	(0.359)	(0.282)	(0.308)	(0.266)	(0.319)	(0.335)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	278	278	278	278	278
R-squared	0.997	0.993	0.986	0.976	0.942	0.926
F statistic	4.533	7.497	9.592	14.14	19.43	20.37

	(7)	(8)	(9)	(10)	(11)	(12)
Year	2007	2008	2009	2010	2011	2012
$\log(AG)$	1.624***	1.692***	1.604***	1.808***	1.870***	1.837***
	(0.340)	(0.364)	(0.349)	(0.457)	(0.469)	(0.479)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	278	278	278	278	278
R-squared	0.914	0.892	0.886	0.815	0.803	0.809
F statistic	20.34	19.68	20.89	14.54	14.34	13.12

	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Year	2013	2014	2015	2016	2017	2018	2019
$\log(AG)$	1.930***	2.062***	1.932***	1.877***	2.329**	2.491**	2.751**
	(0.553)	(0.650)	(0.662)	(0.695)	(0.903)	(1.016)	(1.143)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	278	278	278	278	275	278	277
R-squared	0.797	0.771	0.801	0.820	0.727	0.676	0.620
F statistic	10.28	8.268	6.708	5.536	5.064	4.745	4.254

Note: This table reports for each year, the causal effect of accumulative government spending (depreciated at the rate of 5%) on real GDP, using raw as the instrument for accumulative government spending. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, since $\varepsilon_{c,i,t} \perp (raw_{c,i'}, spillover_{c,i'})$, we have $\varepsilon_{c,t} \perp raw_c$. Therefore, θ_t captures the causal effect of raw_c on the city-wide GDP growth.

□

D.2 Government Spending and Population Density

Table A.4 shows that population density has a large effect on land demand.

Table A.4: Pop. density and land demand

	(1)	(2)	(3)	(4)
Dep Var	log(LandSupply)	log(LandPrice)	log(LandSupply)	log(LandPrice)
popden	9.865***	5.725***	2.485***	3.828***
	(16.53)	(16.55)	(6.714)	(12.07)
log(DownTown)			0.456***	0.143***
			(20.05)	(12.52)
log(GDP/POP)			0.399***	0.0386
			(11.51)	(1.433)
Prov-Year FE	Yes	Yes	Yes	Yes
Observations	28,967	28,967	28,967	28,967
R-squared	0.359	0.486	0.531	0.515
#Sub-city	2147	2147	2147	2147

Note: This table shows the correlation between raw and the log of total land supply and average land price for each sub-city during 2007-2019. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.3 plots the population density of the satellite sub-cities against the population density of the central sub-city.

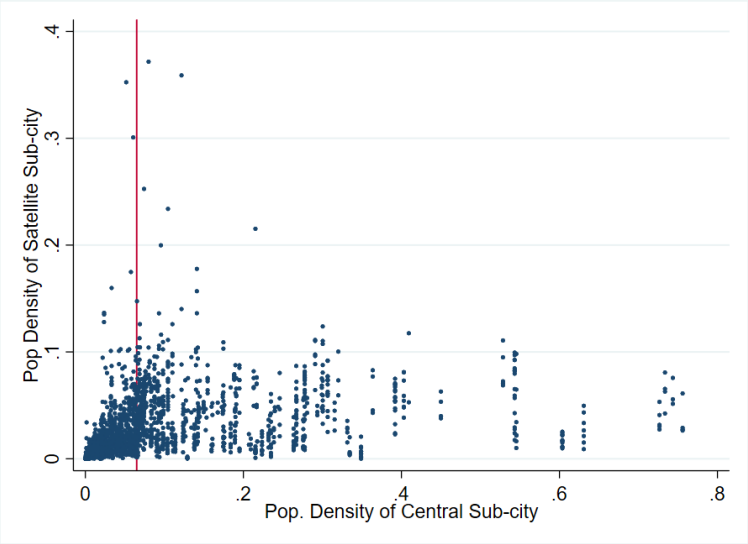

Figure A.3: Population Density of central and satellite sub-cities

Note: The graph plots the population density of the satellite sub-cities against that of the central sub-city, both measured in 2000.

E Supplementary material for Section 6

E.1 Estimation of Production Function and TFPQ

For simplicity, I will ignore $Z_{k,j,t}$ and $C_{k,j,t}$ from Equation (18) and write the log TFPQ as follows:

$$tfpq'_{k,j,t} = \log(Q_{k,j,t}) - \alpha^j_m \cdot \log(M_{k,j,t}) - \alpha^j_l \cdot \log(L_{k,j,t}) - \alpha^j_k \cdot \log(K_{k,j,t}) \tag{23}$$

In Equation (23), $Q_{k,j,t}$ is the firm k's sale in year t measured in fixed price in 1990, $M_{k,j,t}$ is material, $L_{k,j,t}$ is employment, and $K_{k,j,t}$ is capital stock. Assume constant return to scale technology, I can then proxy the input elasticity using the cost share of the input:

$$\alpha^j_m = \bar{S}^m_{j,t},\ \alpha^j_l = \bar{S}^l_{j,t},\ \alpha^j_k = 1 - \bar{S}^m_{j,t} - \bar{S}^l_{j,t},$$

where $\bar{S}^m_{j,t}$ is the share of materials in revenues and $\bar{S}^l_{j,t}$ is the share of labor wages in revenues, for the industry j in year t.

In the Annual Survey of Industrial Firms data, sales measured in the fixed price in 1990 are only available for the period 1998-2003, but sales measured in the current price is

always available during the whole period 1998-2007. To get an estimate of the fixed-price sales for 2004-2007, I calculate the output weighted average log price for each industry in each city during 2001-2003, and then combine the average price with the current-price sales to estimate the fixed-price sales for 2004-2007.

Specifically, denote sales measured in current prices as R_{it}, I then adjust the price as follows.

$$p_{c,j} = \sum_{k,t} \log(\frac{R_{k,j,t}}{Q_{k,j,t}}) \cdot \frac{Q_{k,j,t}}{\sum_{k,t} Q_{k,j,t}} \ , t \in \{2001, 2002, 2003\}$$

$$\log(Q_{k,j,t}) = \log(R_{k,j,t}) - p_{c(k),j} \ , t \in \{2004, 2005, 2006, 2007\}$$

I then subtract the measure of resource utilization from $tfpq'_{k,j,t}$ to get $tfpq_{k,j,t}$:

$$tfpq_{k,j,t} = tfpq'_{k,j,t} - utili_{k,j,t}$$

E.2 Measure Downstream and Upstream Exposure

Denote $Q_{c,i,j}$ as the output of all firms in industry j registered in city c sub-city i in 2000, and $W_{c,i,j}$ as the total intermediate inputs used by firms in industry j registered in city c subcity i in 2000.

Downstream Exposure. For a given firm in industry j_1, the exposure to downstream industries in other sub-cities is the probability that it sells products to firms in other sub-cities. I estimate this probability as the total demand for product j_1 from firms in other sub-cities divided by the total supply of product j_1 from firms in this city.

Formally, denote s_{j_1,j_2} as the use of input j_1 for every 1 RMB of total input used by firms in industry j_2 calculated using China Input-Output Table of 2002. I define the downstream exposure as follows:

$$Downstream_{c,i,j} = \frac{\sum_{i' \neq i} \sum_{j' \neq j} W_{c,i',j'} \cdot s_{j,j'}}{\sum_i Q_{c,i,j}} \tag{24}$$

Upstream Exposure For a given firm in industry j_2, the exposure to upstream industries in other sub-cities is the probability that it buys inputs from firms in other sub-cities. I

estimate this probability as the total supply of each input from firms in other sub-cities divided by the total demand for this input. As firms use multiple inputs, I can calculate the average probability weighted by the share of this input in the firms' total input uses.

Formally,

$$Upstream_{c,i,j} = \sum_{j' \neq j} s_{j',j} \cdot \frac{\sum_{i' \neq i} Q_{c,i',j'}}{\sum_{i_1,j_1} W_{c,i_1,j_1} \cdot s_{j',j_1}} \tag{25}$$