Urban Growth Shadows in Mainland China

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Abstract

Proximity between cities can either foster competition, potentially hindering growth, or promote growth through improved market access. This study delves into the context of economic geography, examining Chinese cities over the past two decades and using data from the China Urban Statistical Yearbook. The research reveals that the presence of "large" cities can cast agglomeration shadows, negatively impacting population and economic growth in nearby smaller cities, with the extent varying by distance. The investigation further explores the underlying mechanisms, including intra-city commuting costs, inter-city commuting costs, and political deprivation effects. Also, using a non-parametric regression, it is found that cities located 222km away from their nearest large city neighbors suffer the most.

Acknowledgement

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Table of Contents

List of Tables

List of Figures

1. Introduction and Related Literature

Beijing stands as a globally renowned megacity, symbolizing prosperity on a grand scale. However, its periphery tells a different story, marked by a poverty belt depicted in red areas in Figure 1, encompassing villages struggling below subsistence levels[1]. The Asian Development Bank (2002) delineates the transformative role of Beijing, drawing migrants from the hinterland to this urban nucleus as barriers from *Hukou* system between cities in China gradually dissolved.

Figure 2 unveils a distinctive C-shaped area surrounding two megacities (Beijing and Tianjin) in yellow in northern China, characterized by a notably sluggish growth pace. A historical parallel is drawn by Cronon (2009), illustrating cities exerting a "gravitational" pull on migrants during the westward expansion of the U.S. This narrative aligns with the perspective that smaller locales neighboring larger cities fall within the "urban shadows", which engenders heightened competition that dampens their growth[2]. Yet, an opposing viewpoint posits that the presence nearby of economic clusters enhances market access or market potential, fostering the growth of adjacent smaller places[3].

This paper endeavors to address this question: does proximity to a large city center impede or promote a location's growth? This empirical investigation is cast within the mainland of China, exploring its development over past two decades. The findings underscore a consistent trend: mega-cities have, over the years, posed challenges to the growth of cities within a radius

[1] Figure 1 illustrates scenarios in 2005, which used the definition from 2000, where a national-level poverty county is defined as a county with an annual output per capita of less than 625 RMB.

[2] See Krugman (1993), Black and Henderson (1999), Cuberes et al. (2021) for agglomeration shadows.

[3] See Glaeser and Kahn (2004), Redding and Sturm (2008) for positive spatial spillovers.

of at least 100 kilometers. This effect persists across various time frames and subsamples, although the coverage of shadow effects varies with different sizes of large center cities. The introduction of high-speed railway (HSR) after 2008 emerges as a mitigating force against the agglomeration shadow effect, while the introduction of ring roads emerges as an intensifying force. Also, China's political urban system hierarchy appears to exacerbate the urban shadows.

Urban economists have examined extensively the theoretical optimal size of cities, emphasizing the tradeoff between agglomeration and congestion effects (Henderson, 1974; Henderson, 1991), and bridged the gap between theory and empirical data (Au & Henderson, 2006). While these studies primarily concentrate on the internal dynamics of cities and cross-sectional properties, such as city number and emergence (Henderson & Ioannides, 1981), and the distribution law of urban size within a country (Ioannides & Overman, 2003; Davis & Weinstein, 2002; Mori et al., 2020), they tell little about why cities are where they are and do not help us to "look intelligently " at map (Krugman, 1993). To address the spatial interactions within urban systems (Ioannides, 2012), economists have turned to the New Economic Geography (NEG).

New Economic Geography (Fujita et al., 2001) offers an evolutionary perspective, extending Christaller’s (1933) model and Krugman's (1991) initial advantage (Fujita & Mori, 1997). It introduces centripetal forces from economic spillovers and dispersal forces induced by increased competition driven by proximity desires of firms (Combes, 2000). This paper specifically focuses on the agglomeration shadow, a phenomenon resulting from the combination of centripetal and dispersal forces. As economic integration deepens and transportation costs decrease, larger cities attract more firms and workers from nearby smaller

Figure1: Poverty Belt

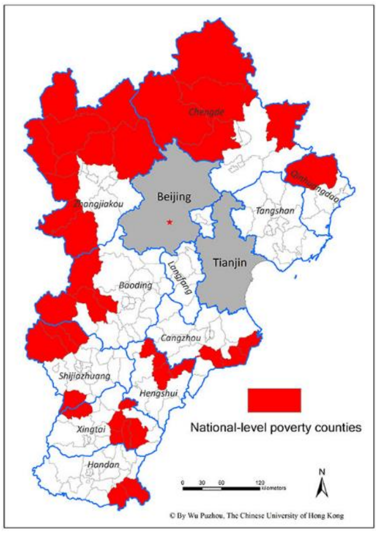
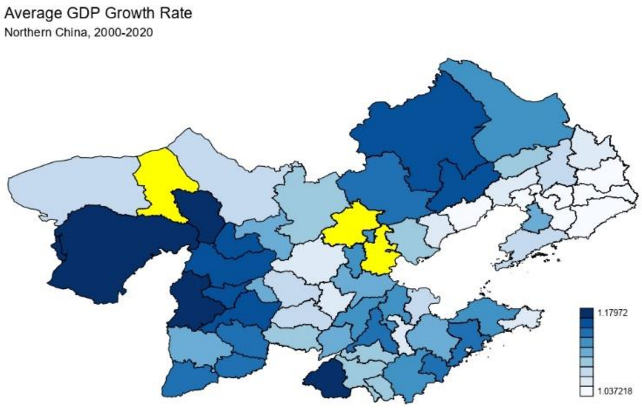


Figure2: City GDP Growth Rate in Northern China



Note: Figure 1 is from Pu Wuzhou, The Chinese University of Hong Kong.

ones, creating a shadow effect that prevents cities from emerging too closely to avoid competition. NEG predicts a positive relationship between population growth and the distance from larger-sized urban centers, leading to a hierarchical structure of cities based on market potential.

In addition to traditional NEG, modern quantitative spatial economics has provided unique insights. Quantitative spatial models have enhanced economists' understanding of economic geography models, addressing issues such as the uniqueness and existence of equilibria, one-to-one mapping from observed data to exogenous primitives, and counterfactual analysis. Theoretical mechanisms, including market access (Redding & Sturm, 2008), spatial linkages (Caliendo et al., 2018), spatial frictions (Desmet & Rossi-Hansberg, 2013; Behrens et al., 2014), innovation patterns (Desmet & Rossi-Hansberg, 2014), migration (Desmet et al., 2018), climate change (Desmet & Rossi-Hansberg, 2015), and international trade (Nagy, 2016), have been identified as quantitatively important.

Recent empirical research has explored spatial interactions among cities in terms of geographic distances (Cuberes et al., 2021; Dobkins & Ioannides, 2001; Chen et al., 2014), the role of history and initial conditions (Black & Henderson, 1999; Dobkins & Ioannides, 2001), echelons in the urban hierarchy (Partridge et al., 2009), market potentials (Hanson, 2005) and process of urbanization over thousands of years (Ioannides & Wei, 2023). These interactions have effects on agglomeration economies (Hanson, 2001), population dynamics (Partridge et al., 2009), unemployment (Overman & Puga, 2002) and wage and income distributions (Quah, 1996; Brülhart & Koenig, 2006; Knaap, 2006) among cities. This paper would focus on the economic growth and population growth of cities, in the context of both economic geography (geographical distances) and urban hierarchies.

There are three papers that are most related to mine. Cuberes et al. (2021) investigate urban growth shadows in the context of the U.S., while my paper explores the Chinese context and introduces inter-city commuting, which has not been empirically explored in their paper. Chen (2014) investigates economic geography in China by regressing growth rates on distances to the nearest large cities. This paper revisits their findings by using better controls and comparing them with the findings from applying the empirical framework from Cuberes et al. (2021) to China. Baum-Snow et al. (2017) discuss the roles of ring roads and railways in the decentralization of Chinese cities. Their work concentrates on the spatial interaction within city prefectures, while my paper focuses on the spatial interaction between city prefectures via transportation systems.

2. Background and Data

Over the past two decades, China has undergone a notable transformation by gradually dismantling the household registration (hukou) system, a move that has effectively reduced restrictions on people's mobility and expanded individual choices (Chan, 2019). The implementation of market-oriented reforms in 1992, as documented by Poncet (2003), has further propelled China's economic growth and transformation, marking its rapid industrialization. In 2008, China's industrial value-added constituted 47.4% of its GDP, surpassing the respective shares observed in the United States and Europe. The substantial presence of manufacturing in the Chinese economy, coupled with the availability of high-quality city-level data (Au & Henderson, 2006), positions China as an ideal laboratory for testing theories of New Economic Geography.

This research relies on data obtained from the China City Statistical Yearbook, which is provided by the National Bureau of Statistics of China (2020). The original statistics, initially in a printed format, underwent transformation into tables. Following the process of recoding and merging, a comprehensive dataset was created, encompassing 291 cities and spanning the years from 2000 to 2020[4]. This dataset includes a wide range of indicators related to the local economy, such as economic, population, and amenities data. All nominal data have been adjusted to real values using the provincial-level CPI. The total observation number is 5,037. Information concerning ring-roads, highways, and normal-speed railways was sourced from the ACASIAN Data Center and China Railway Statistical Yearbook. The location details of

[4] It is an unbalanced panel.

cities were sourced from the National Earth System Science Data Center. Data regarding high-speed railways (HSR) in mainland China is sourced from Gaotie Web (2024), a Chinese website dedicated to tracking the construction of HSR. Data on transportation system in 1962 is from Baum-Snow et al. (2017). See Table A1 and Table A2 in Appendix 1 for summary statistics of key variables.

Given the changes in administrative boundaries for cities in mainland China, the border lines between cities in 2015 are employed as the baseline. In instances where an old single city was subdivided into new administrative entities, they are consolidated into the original city and treated as a single entity. Conversely, when two old separate cities were merged into a new single entity, they are treated as the new entity from the beginning in the dataset. Similarly, for areas that underwent name and administrative code changes, old observations are renamed using the updated information. It is important to note that these adjustments apply only to a small fraction of cities[5].

By leveraging the location information and economic data of cities for each year, I designate large cities in the dataset. Consistent with the approach outlined in Cuberes et al. (2021), cities surpassing the 95th and 99th percentiles of population in a given year are categorized as "moderately large cities" and "very large cities," respectively[6]. Population in the whole prefecture is used. It is crucial to note that, due to the annual fluctuation in population

[5] In my version of data, only Chaohu, Simao, Hailaer, Huaiyin, Laiwu had changed.

[6] In each year, the list of moderately large cities also contains very large cities.

rankings, the specific cities qualifying as moderately large and very large may vary from year to year.

3. Methodology and Baseline Regression Results

I aim to examine the impact of proximity to large cities on city growth. Therefore, the variables of interest will be the proximity to large cities. Following Bosker and Buringh (2017) and Cuberes et al. (2021), I construct the following dummy variables: $I_{\mathrm{it}}^{\mathrm{DL}}$. Where i denotes a city, and $I_{\mathrm{it}}^{\mathrm{DL}}$ is a vector of dummy variables, taking 1 if for city i at year t, there is at least one location, $k \neq i$, within a certain distance range D of location i, that has population above a certain level L, and no such location within a smaller distance[7]. For large cities themselves, the dummies are all zero. For detailed information on the construction of these dummy variables, please refer to Appendix 2.

In section 2, large cities are categorized as either moderately large cities or very large cities. Here, thresholds L are defined as the 95th percentile or 99th percentile of population for each year, respectively, for the two levels of large cities. Distances D are divided into six bands: {0km-50km, 50km-100km, 100km-150km, 150km-200km, 200km-250km, 250km-300km}. In the extension part, I estimate the location of the minimum growth rate from large cities, and it falls within 300km. Also, this ensures that within each interval, there are sufficient

[7] The rationale for ensuring the absence of a large neighbor within a narrower bandwidth is to employ these dummy variables for isolating the partialized effects of large neighbors within a specific range. If there is a large city within the 200-250km band, it is crucial to ensure that the dummy variables capture the pure effect from a large neighbor within this range, rather than being influenced by another central city in a closer band, such as 100-150km.

observations to assign a value of 1 for each key dummy variable [8]. For example, $I_{\text{X 2008}}^{\text{100−150km very}}$ would take the value of 1 if for city X in 2008 there is at least another city within the distance of 100-150km, that has a population above 99 percentiles of that year, and there is no such location within 100 km. Note that these dummy variables are time-varying as the designations of large cities change each year. Essentially, for each level of large neighbors, I have categorized cities into seven types based on the distance to the nearest large neighbor: those with at least one large neighbor within 50 km, in the intervals of 50-100 km, 100-150 km, 150-200 km, 200-250 km, 250-300 km, and those without any large neighbor within 300 km. According to the summary statistics in Table A3 in Appendix 1, 12.3% of the entire city sample has a very large neighbor within 300 km, and 41.4% of the entire city sample has a moderately large neighbor within 300 km. In the regression output tables, the relationship between the displayed variables and the dummies in the regression equation is as follows:

Variables			
Regression Tables	Equation	Regression Tables	Equation
$I(v, 50km)$	$I_{it}^{\text{0−50km very}}$	$I(m, 50km)$	$I_{it}^{\text{0−50km moderately}}$
$I(v, 100km)$	$I_{it}^{\text{50−100km very}}$	$I(m, 100km)$	$I_{it}^{\text{50−100km moderately}}$
$I(v, 150km)$	$I_{it}^{\text{100−150km very}}$	$I(m, 150km)$	$I_{it}^{\text{100−150km moderately}}$
$I(v, 200km)$	$I_{it}^{\text{150−200km very}}$	$I(m, 200km)$	$I_{it}^{\text{150−200km moderately}}$
$I(v, 250km)$	$I_{it}^{\text{200−250km very}}$	$I(m, 250km)$	$I_{it}^{\text{200−250km moderately}}$
$I(v, 300km)$	$I_{it}^{\text{250−300km very}}$	$I(m, 300km)$	$I_{it}^{\text{250−300km moderately}}$

[8] Although many regressions omit dummy variables within 50km (shown as dashed lines), some do not. According to Tables A3 and A4, in 2000 no city had large neighbor within 50 km but some became to have afterwards.

I first conduct cross-sectional regressions, with growth rates being the geometrically averaged growth across 20 years and dummy variables being those from the beginning year 2000[9]. The regression equation is as follows:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{i},2000}^{\mathrm{DL}} + \boldsymbol{X_{0\,\mathrm{i}}}\theta + \boldsymbol{X_{1\,\mathrm{i}}}\delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}} ,$$

where i denotes a location, and β_{D}^{L} are coefficients of interest; $\boldsymbol{X_{0\,\mathrm{i}}}$ is a vector of geographical controls, including polynomials of longitudes and latitudes (up to third orders and their interactions); $\boldsymbol{X_{1\,\mathrm{i}}}$ is a vector of economic characteristics controls from 1990[10]; and $\omega_{\mathrm{province}}$ is province fixed effect. Regressions are conducted separately for moderately large cities and very large cities. Cuberes et al. (2021) use cross-sectional regressions controlling only geographical characteristics. Thus, I first report regressions only using geographical controls in Table 1 and Table 2. Then in Table 3 and Table 4, regressions with province fixed effects and all sets of controls are reported. In all tables, the third and fourth columns show the results for cities with populations below the 80th percentile in 2000, defined as "small" cities.

The baseline regression results are reported in Tables 1 and 2[11]. In Table 1 for very large cities, examining the first and third columns reveals that, compared to cities having their nearest

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[9] Moderately large cities in that year are: Shanghai, Linyi, Baoding, Beijing, Nanyang, Zhoukou, Haerbin, Tianjin, Xuzhou, Chengdu, Shijiazhuang, Chongiqng, and Fuyang; very large cities are Beijing, Chongging and Shanghai.

[10] The cross-sectional regressions incorporate a set of economic control variables. To mitigate endogeneity, I draw the controls from 1990 city statistics, instead of using statistics after 2000. These controls encompass city-level GDP, population, economic density, population density, FDI amount, proportion of population with above high school education, government spending, and investment.

[11] In the regression tables, dashed lines represent omitted variables. In this paper, while many regressions omit dummy variables within 50 km, some do not, so I have retained that variable in each table.

large neighbor over 300km away, both population and economic growth of cities are negatively associated with proximity to very large cities, with the most significant negative effects observed in the 150-200 km band, amounting to -0.47% and -0.62%, respectively. This substantiates the existence of agglomeration shadows. This effect is substantial, especially when compared to the mean of averaged annual population growth rates for all cities in the dataset, which is nearly 0.7%. Such negative effects are also observed in the 50-100km, 200-250km, and 250-300km bands for both population growth and economic growth, except that in the 50-100km band, economic growth enjoys positive spillovers. In the second and fourth columns, only small cities, defined as falling below the 80th percentile of population in 2000, are included in the regressions. Notably, small cities actually suffer more from the agglomeration shadows. For intervals beyond 150 km, the negative effects small cities experience are almost 50% larger than those observed for the whole sample. For moderately large cities in Table 2, the agglomeration shadow effects on population and economic growth are present as well, with the most apparent effects observed in the 150-200 km band, although the magnitude of coefficients is smaller than those in the very large city regressions. In a nutshell, urban growth shadows exist, and very large cities in this context could cast stronger agglomeration shadows over greater distances than moderately large cities.

Reported in Tables 3 and 4 are regressions with all sets of controls and province fixed effects, showing that the previous results remain robust under this framework. Additionally, for robustness checks, I use panel regressions to examine the patterns of urban growth shadows.

Table 1: Baseline Cross-Sectional Regressions for Very Large Cities, with Geographical Controls

VARIABLES	(1) Population Growth	(2) GDP Growth	(3) Small Subsample: Population Growth	(4) Small Subsample: GDP Growth
$I(v, 50km)$	-	-	-	-
$I(v, 100km)$	-0.0046***	0.0126**	-0.0034*	0.0108**
	(0.0014)	(0.0051)	(0.0019)	(0.0050)
$I(v, 150km)$	0.0064	0.0010	0.0074	-0.0022
	(0.0054)	(0.0033)	(0.0058)	(0.0040)
$I(v, 200km)$	-0.0047**	-0.0133***	-0.0062**	-0.0124***
	(0.0022)	(0.0034)	(0.0027)	(0.0044)
$I(v, 250km)$	-0.0040*	-0.0089	-0.0068***	-0.0107
	(0.0021)	(0.0079)	(0.0020)	(0.0113)
$I(v, 300km)$	-0.0035*	-0.0125**	-0.0051**	-0.0170***
	(0.0020)	(0.0047)	(0.0024)	(0.0045)
Constant	0.2249	0.5687	0.4095	0.7302
	(0.8060)	(1.9227)	(0.8506)	(2.1179)
Observations	289	289	235	235
R-squared	0.251	0.353	0.289	0.365

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include geographical control variables.

Table 2: Baseline Cross-Sectional Regressions for Moderately Large Cities, with Geographical Controls

VARIABLES	(1) Population Growth	(2) GDP Growth	(3) Small Subsample: Population Growth	(4) Small Subsample: GDP Growth
$I(m, 50km)$	-	-	-	-
$I(m, 100km)$	-0.0030	-0.0012	-0.0027	-0.0025
	(0.0022)	(0.0043)	(0.0026)	(0.0047)
$I(m, 150km)$	0.0002	-0.0038	0.0001	-0.0055
	(0.0040)	(0.0047)	(0.0059)	(0.0063)
$I(m, 200km)$	-0.0035**	-0.0056*	-0.0043***	-0.0058*
	(0.0015)	(0.0031)	(0.0015)	(0.0034)
$I(m, 250km)$	-0.0009	-0.0053	0.0014	-0.0068
	(0.0011)	(0.0051)	(0.0021)	(0.0070)
$I(m, 300km)$	-0.0003	-0.0011	-0.0017	-0.0089
	(0.0019)	(0.0052)	(0.0027)	(0.0057)
Constant	0.2322	0.1455	0.2879	0.1599
	(0.7879)	(1.8596)	(0.7831)	(2.0518)
Observations	289	289	235	235
R-squared	0.234	0.343	0.263	0.356

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include geographical control variables.

Table 3: Baseline Cross-Sectional Regressions for Very Large Cities, with All Controls

VARIABLES	(1) Population Growth	(2) GDP Growth	(3) Small Subsample: Population Growth	(4) Small Subsample: GDP Growth
$I(v, 50km)$	-	-	-	-
$I(v, 100km)$	-0.0051*	0.0253***	-0.0051	0.0277**
	(0.0030)	(0.0060)	(0.0034)	(0.0105)
$I(v, 150km)$	-0.0010	0.0111***	-0.0004	0.0135**
	(0.0036)	(0.0034)	(0.0041)	(0.0053)
$I(v, 200km)$	-0.0039**	-0.0016	-0.0045**	0.0014
	(0.0015)	(0.0020)	(0.0018)	(0.0047)
$I(v, 250km)$	-0.0021	0.0029	-0.0026	-0.0017
	(0.0025)	(0.0040)	(0.0036)	(0.0053)
$I(v, 300km)$	-0.0018	-0.0036	-0.0040	-0.0057
	(0.0022)	(0.0039)	(0.0027)	(0.0054)
Constant	-0.5979	-2.2182	-0.4511	-2.4234
	(1.0004)	(2.1105)	(0.8379)	(2.1383)
Observations	245	245	199	199
R-squared	0.603	0.669	0.663	0.700

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include province fixed effects, as well as geographical and economic control variables.

Table 4: Baseline Cross-Sectional Regressions for Moderately Large Cities, with All Controls

VARIABLES	(1) Population Growth	(2) GDP Growth	(3) Small Subsample: Population Growth	(4) Small Subsample: GDP Growth
$I(m, 50km)$	-	-	-	-
$I(m, 100km)$	-0.0017	-0.0056	-0.0039	-0.0066
	(0.0021)	(0.0060)	(0.0035)	(0.0088)
$I(m, 150km)$	-0.0037*	-0.0056*	-0.0083*	-0.0097*
	(0.0019)	(0.0030)	(0.0047)	(0.0050)
$I(m, 200km)$	-0.0033**	-0.0070***	-0.0048**	-0.0090**
	(0.0015)	(0.0023)	(0.0019)	(0.0033)
$I(m, 250km)$	-0.0012	0.0018	-0.0036*	-0.0038
	(0.0012)	(0.0043)	(0.0020)	(0.0043)
$I(m, 300km)$	-0.0009	-0.0019	-0.0029***	-0.0046
	(0.0012)	(0.0050)	(0.0008)	(0.0061)
Constant	-0.7960	-2.1635	-0.4812	-2.5613
	(0.9737)	(2.3747)	(0.6964)	(2.4141)
Observations	245	245	199	199
R-squared	0.605	0.660	0.672	0.687

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include province fixed effects, as well as geographical and economic control variables.

4. Mechanisms and Extensions

In this section, I will delve into the economic mechanisms through which large cities impact surrounding areas. The exploration will encompass the roles of inter-city and intra-city transportation, geographical distances, and the urban political hierarchy within China.

4.1 Inter-city and Intra-city Commuting Cost and Traffic Networks

4.1.1 Inter-city Commuting Cost and High-Speed Railways

Transportation networks between cities could be, by influencing market access, an important channel through which small locations are affected by spillover or shadow effects, among which the followings matter most[12]: railway infrastructure (Donaldson & Hornbeck, 2016), establishment of canals (Shaw 1990), development of the highway system (Baum-Snow, 2007; Allen & Arkolakis, 2014), and high-speed railway (Zheng & Kahn, 2013; Lin, 2017).

In the recent decades of China's development, the significance of the highway and high-speed railway (HSR) has grown considerably. The Chinese highway system has been observed to contribute to the reduction in growth for peripheral counties (Faber, 2014; Baum-Snow et al., 2020). Notably, in China, the high-speed railway, which is three times faster than the conventional railway on average, has had a positive impact on some small cities that are situated far from large urban centers. Dong et al. (2021) demonstrate that market access is a crucial factor preventing these locations from turning into "ghost cities."

[12] Bernhofen et al. 2016 studies the effect of the implementation of containerization.

The reduction in commuting costs has also empowered hinterlands to influence their larger neighbors. Zheng and Kahn (2012) highlight that China's bullet trains alleviate the costs associated with the growth of megacities, such as congestion, by enabling people who work in mega-cities to reside in surrounding smaller cities. Baum-Snow et al. (2017) discover that ring roads and railways not only contribute to the decentralization of central cities but also foster the prosperity of surrounding regions within the same prefecture.

Transportation networks play a dual role in influencing both commodity shipping costs and passenger commuting costs. Glaeser and Kahn (2004) suggest that in recent decades, the evolution of cities has been primarily affected by the latter. Consequently, this paper focuses on the fall of commuting costs affecting workers, and encompasses the construction of subways and ring roads within cities and High-Speed Railway (HSR) connections between cities.

The data on high-speed railway is obtained from Gaotie.cn, which offers information on the construction timeline of each HSR station in every city prefecture. Using this data, I construct an indicator variable: HSR_i, that takes the value of 1 if a city already has a station within its urban area. Consequently, I create a city panel of dummy variables that provide information on HSR. Since Mainland China began building the HSR system in 2008 expansion, I may only use data from the year 2008 onwards in this section.

Here, I will initially discuss the results using these dummy variables. In robustness check, I also use another empirical framework which incorporates market access indicators. I firstly run the following cross-sectional regression:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \alpha_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}}\, HSR_{i}^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + HSR_{i} + \boldsymbol{X}_{\mathbf{2\,i}}\delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}}\,,$$

where HSR_{i}^{DL} takes 1 if this city i becomes connected (from not connected) to at least one of its large neighbor over level L in the band D by High-Speed Railway in this period. My focus lies on the coefficients α_{D}^{L} of the interaction terms $I_{\mathrm{i}}^{\mathrm{DL}} HSR_{i}^{DL}$; $X_{2\,\mathrm{i}}$ is a vector of economic control variables[13]. In the regression, I also include the dummy variable indicating whether city i itself is connected by HSR. Note that I employ cross-sectional regression to estimate the effect of HSR on averaged city growth rates over the entire period. In the robustness check, I also report a panel regression. The results for very large cities are displayed in Table 5[14].

[13] The same controls as in the baseline cross-sectional regressions, excluding FDI amount, proportion of population with above high school education.

[14] For instance, in the table, $HSR(v, 100km)$ is one of the interaction terms and takes 1 if a city becomes connected by HSR with a very large city neighbor within 100km in this period.

Table 5: HSR Cross-Sectional Regressions for Very Large Cities, not using IV

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(v, 50km)$	-	-
$I(v, 100km)$	-0.0761***	-0.0553***
	(0.0034)	(0.0059)
$I(v, 150km)$	-0.0082***	0.0038
	(0.0030)	(0.0074)
$I(v, 200km)$	-0.0065**	0.0061
	(0.0027)	(0.0124)
$I(v, 250km)$	-0.0101***	0.0130
	(0.0020)	(0.0127)
$I(v, 300km)$	-0.0086**	-0.0055*
	(0.0035)	(0.0029)
$HSR(v, 100km)$	0.0533***	0.0224***
	(0.0008)	(0.0053)
$HSR(v, 150km)$	0.0082**	0.0279**
	(0.0039)	(0.0111)
$HSR(v, 200km)$	-0.0052	-0.0077
	(0.0037)	(0.0127)
$HSR(v, 250km)$	0.0013	-0.0052
	(0.0015)	(0.0059)
$HSR(v, 300km)$	0.0010	-0.0067
	(0.0020)	(0.0052)
HSR	0.0010	-0.0019
	(0.0015)	(0.004)
Constant	-0.0224**	0.1772***
	(0.0090)	(0.0140)
Observations	291	291
R-squared	0.359	0.452

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include economic control variables.

I use data on the times when each city was connected to High-Speed Rail (HSR); however, utilizing this information directly in regressions poses endogeneity issues. Specifically, employing ordinary least squares (OLS) regressions to compare "treated" (connected to HSR) and "untreated" (not connected to HSR) locations may not consistently estimate the causal effect of transport improvement due to non-random selection of locations into the treatment group (Redding & Turner, 2015). Planners, when deciding which cities to connect to HSR, likely considered the economic development level and potential of each location. Common solutions involve instrumental variables, often derived from the "planned route method" (Faber, 2015) or historical and military transportation network information (Baum-Snow et al., 2017).

In this study, I employ railways data from 1962 in China as instrumental variables (IV). The rationale is that between 1949 and 1962, a significant portion of railroad investment was influenced by the Soviet Union and aimed to link resource-rich regions in China’s west with manufacturing centers in the east. It is plausible that much of the rail network was constructed without consideration for its possible impact on the future, which is the post-1990 internal reorganization of cities (Baum-Snow et al., 2017). The first stage regressions are as follows:

$$I_{\mathrm{i}}^{\mathrm{DL}} HSR_i^{DL} = \sum_{D=[0km,50km]}^{[250km,300km]} \mu_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}}\, Rail1962_i^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \varphi_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{2\,i}}\delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}}\ ,$$

where $Rail1962_i^{DL}$ takes the value of 1, if for city i and any of its large neighbors over level L in the band D are connected by railway in year 1962. For instance, the first stage regressions for very large cities are shown in Table 6[15]. The results are coherent: the connectivity of a city to a large city within specific distance intervals by High-Speed Railway (HSR) is predicted by its connectivity to any large city within corresponding intervals by railway in 1962. The final column shows the first stage, which instruments HSR_i, a dummy variable indicating city i's connectivity to HSR.

The instruments pass weak instrument tests. Thus, the second stage should be:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \alpha_{\mathrm{D}}^{L} \left(I_{\mathrm{i}}^{\mathrm{DL}} \widehat{HSR_i^{DL}}\right) + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{2}\,\mathbf{i}}\delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}} \,,$$

Table 7 and Table 8 report the results for very large cities and moderately large cities. The findings reported by Table 7 from the regression using very large cities indicate that within 250 kilometers, the introduction of High-Speed Rail (HSR) alleviates the agglomeration shadow for population growth. For a city, the presence of a very large neighbor within 250km still influences negatively its own population growth. However, when this city is connected to its large neighbor by HSR, it experiences an advantageous shock in population. Note that this advantageous shock only reduces the magnitude of the negative effects for distance within 100km, as the sum of the interaction term and dummy variable in certain distance intervals remains negative. The coefficient for the dummy indicating whether each city itself becomes connected by HSR is not significant, indicating that HSR primarily affects cities through their large neighbors. For moderately large cities, the alleviation effect of HSR on population still

[15] In the table, $Rail1962$ is the historical dummy instrument indicating whether this city was connected by railway itself in 1962. $Rail1962(v, 50km)$ is the historical instrument indicating whether this city was connected by railway to any of its very large neighbors within (x-50, x) kilometers in 1962.

exists, but less pronounced. This observation agrees with the predictions of economic geography models, where large cities attract labor from small surrounding locations. If commuting between large city centers and small surrounding areas becomes less costly in terms of time and money, labor may choose to reside in small locations at lower costs while still enjoying high wages, consumption, and the amenities of large city centers. There is no evidence to suggest that the presence of High-Speed Rail (HSR) has a significant effect on the economic growth of cities, once the effects of HSR connecting cities with their neighbors are isolated. This suggests that HSR primarily impacts cities by enhancing connectivity with their neighboring areas.

Table 6: HSR Cross-Sectional Regressions for Very Large Cities, IV first stage

VARIABLES	(1) $HSR(v, 100km)$	(2) $HSR(v, 150km)$	(3) $HSR(v, 200km)$	(4) $HSR(v, 250km)$	(5) $HSR(v, 300km)$	(6) HSR
$Rail1962$	-0.0030	-0.0008	0.0011	-0.0011	-0.0047	0.0865***
	(0.0052)	(0.0094)	(0.0106)	(0.0117)	(0.0136)	(0.0237)
$Rail1962(v, 50km)$	-	-	-	-	-	-
$Rail1962(v, 100km)$	0.2501***	0.1063**	0.1059*	0.1060*	0.1061	0.0802
	(0.0285)	(0.0516)	(0.0584)	(0.0640)	(0.0747)	(0.1300)
$Rail1962(v, 150km)$	0.0000	0.1428***	-0.0083	-0.0083	-0.0083	-0.0101
	(0.0139)	(0.0252)	(0.0285)	(0.0313)	(0.0365)	(0.0636)
$Rail1962(v, 200km)$	0.0002	0.0001	0.1511***	-0.0325	-0.0322	-0.0369
	(0.0139)	(0.0252)	(0.0285)	(0.0313)	(0.0365)	(0.0636)
$Rail1962(v, 250km)$	0.0003	0.0006	0.0006	0.1845***	0.0526	0.0576
	(0.0144)	(0.0260)	(0.0294)	(0.0323)	(0.0376)	(0.0655)
$Rail1962(v, 300km)$	-0.0029	-0.0086	-0.0098	-0.0118	0.1164***	-0.0095
	(0.0097)	(0.0176)	(0.0199)	(0.0219)	(0.0255)	(0.0444)
Constant	0.0154*	0.0367**	0.0400**	0.0503**	0.0711***	0.5017***
	(0.0088)	(0.0159)	(0.0180)	(0.0197)	(0.0230)	(0.0400)
Observations	272	272	272	272	272	272
R-squared	0.249	0.218	0.298	0.343	0.299	0.055

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include economic control variables, and dummy variables indicating the presence of large cities in different intervals, which are all the other variables in the second stage.

Table 7: HSR Cross-Sectional Regressions for Very Large Cities, IV 2nd stage

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(v, 50km)$	-	-
$I(v, 100km)$	-0.1792***	-0.2247
	(0.0662)	(0.3374)
$I(v, 150km)$	-0.0098***	0.0027
	(0.0032)	(0.0151)
$I(v, 200km)$	-0.0016	-0.0269***
	(0.0016)	(0.0068)
$I(v, 250km)$	-0.0119**	0.0524***
	(0.0054)	(0.0113)
$I(v, 300km)$	0.0019	-0.0416***
	(0.0019)	(0.0052)
$HSR(v, 100km)$	0.1693**	0.2280
	(0.0696)	(0.3592)
$HSR(v, 150km)$	0.0156**	-0.0016
	(0.0066)	(0.0306)
$HSR(v, 200km)$	-0.0129	0.0737***
	(0.0087)	(0.0218)
$HSR(v, 250km)$	0.0185***	-0.1163***
	(0.0064)	(0.0387)
$HSR(v, 300km)$	-0.0044	0.0612*
	(0.0046)	(0.0367)
HSR	-0.0061	0.0842
	(0.0066)	(0.0570)
Constant	0.0043	0.1366***
	(0.0038)	(0.0082)
Observations	272	272

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include economic control variables.

Table 8: HSR Cross-Sectional Regressions for Moderately Large Cities, IV 2nd stage

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(m, 50km)$	-	-
$I(m, 100km)$	-0.0139*	0.0024
	(0.0074)	(0.0024)
$I(m, 150km)$	-0.0045	-0.0027
	(0.0079)	(0.0027)
$I(m, 200km)$	-0.0151**	-0.0032
	(0.0066)	(0.0020)
$I(m, 250km)$	-0.0065	-0.0007
	(0.0055)	(0.0025)
$I(m, 300km)$	0.0012	-0.0017
	(0.0082)	(0.0036)
$HSR(m, 100km)$	0.0061	-0.0101***
	(0.0058)	(0.0036)
$HSR(m, 150km)$	-0.0010	-0.0101***
	(0.0124)	(0.0033)
$HSR(m, 200km)$	0.0004	-0.0051**
	(0.0070)	(0.0025)
$HSR(m, 250km)$	0.0202*	-0.0048
	(0.0107)	(0.0028)
$HSR(m, 300km)$	-0.0162	-0.0045
	(0.0104)	(0.0045)
HSR	0.0228	0.0005
	(0.0245)	(0.0443)
Constant	0.1460***	0.0080***
	(0.0072)	(0.0028)
Observations	272	272

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include economic control variables.

4.1.2 Intra-city Commuting Cost and Ring Roads in Large Cities

Inter-city commuting cost is crucial for the internal structure of cities (Lucas & Rossi-Hansberg, 2003). Baum-Snow et al. (2017) study the decentralization of population and economic activities within Chinese cities over the past decades. In contrast, Cuberes et al. (2021) show that the reduction of intra-city commuting cost in a central city also has implications for its neighboring cities: the introduction of automobiles in large city centers exacerbated the growth shadows in population that surrounding cities experienced. Therefore, I will also explore the role of intra-city commuting cost in the context of urban growth shadows in Mainland China.

Ring roads in China typically encircle a prefecture city. They are primarily designed to reduce traffic volumes in the urban center. Thus, ring roads could, to some extent, proxy a center city's intra-city commuting cost. Using data from the ACASIAN Data Center, I obtain a cross-sectional dataset that provides information on whether a city had ring roads in the year 2010. Similar to the regression of HSR, following Cuberes et al. (2021)[16], this regression is conducted[17]:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \alpha_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}}\, Ring_i^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{2}\ \mathbf{i}}\delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}}\ ,$$

where $Ring_i^{DL}$ takes 1 if this city i has any of its large neighbor over level L in band D

[16] Cuberes et al. (2021) conducted a similar regression, using the introduction of automobiles and trams in the central large city as indicators of intra-city commuting.

[17] Observations used are identical to the HSR section, starting at 2008.

with ring roads in 2010. I focus on the coefficients α_{D}^{L} of the interaction terms; $X_{2\,\mathrm{i}}$ is a vector of control variables[18]. Results are presented in Table 9[19]. I do not report the results for very large cities because many of the newly added ring road variables are omitted in the regressions.

I find that moderately large cities, within 250 km, the presence of ring roads exacerbates the agglomeration shadow effects they cast on the surrounding areas. When people working in large city centers find it easier to commute within the large cities, relative to commuting from a nearby city to this city center, they tend to live in the peripheral part of the city center at lower cost instead of residing in a nearby city. This phenomenon contributes to the observed effect[20].

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18 The same as controls in the HSR cross-sectional regressions.

19 In the table, $Ring(m, xkm)$ is the interaction between the moderately large city dummy and the ring road indicator of the moderately large cities within (x-50, x) distance.

20 In Cuberes et al. (2021), a similar effect was observed for U.S. cities in the last century. The study used the adoption of automobiles and trams as indicators for intra-city commuting costs.

Table 9: Ring Roads Cross-Sectional Regressions for Moderately Large Cities

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(m, 50km)$	-	-
$I(m, 100km)$	-0.0101	-0.0077
	(0.0067)	(0.0060)
$I(m, 150km)$	-0.0032	0.0010
	(0.0072)	(0.0068)
$I(m, 200km)$	-0.0152**	-0.0183***
	(0.0056)	(0.0062)
$I(m, 250km)$	-0.0040	-0.0048
	(0.0055)	(0.0059)
$I(m, 300km)$	0.0009	-0.0060
	(0.0072)	(0.0082)
$Ring(m, 100km)$	-0.0013	0.0123
	(0.0052)	(0.0074)
$Ring(m, 150km)$	-0.0136***	-0.0198**
	(0.0044)	(0.0078)
$Ring(m, 200km)$	0.0006	0.0036
	(0.0055)	(0.0066)
$Ring(m, 250km)$	-0.0069	-0.0193**
	(0.0054)	(0.0086)
$Ring(m, 300km)$	0.0136***	0.0259**
	(0.0040)	(0.0098)
Constant	0.1459***	0.1454***
	(0.0076)	(0.0072)
Observations	291	291
R-squared	0.347	0.442

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: regressions in all columns include economic control variables.

4.2 Geographical Distances

The data show that smaller neighbors within a certain distance of large cities exhibit lower growth rates. Consequently, it is interesting to explore the influence of distances on city growth rates. In this context, geographical distances are considered exogenous. Previous empirical investigations by Partridge et al. (2009) and Chen et al. (2014) have explored this question in the context of urban hierarchy in the U.S. and mainland China, respectively. Since distances are time-invariant, I use them in city cross-sectional regressions here. Specifically, I regress the geometric average of growth rates over twenty years on third-order polynomials of distances to the nearest moderately large city in 2000[21]:

$$g_{\mathrm{i}} \;= \beta_1 dist\_big_i + \beta_2 (dist\_big_i)^2 \; + \beta_3 (dist\_big_i)^3 + \boldsymbol{X}_{\mathbf{3\ i}} \delta + \omega_{\mathrm{province}} + \epsilon_{\mathrm{i}} \;,$$

where $\boldsymbol{X}_{\mathbf{3\ it}}$ represents a vector of control variables[22]. The regression results are reported in Table 10 and Table 11, where the second column including control variables.

The baseline regression confirms that the presence of a moderately large city within a certain distance has negative impact on cities' population growth. The regressions using polynomials of distances actually provide a continuous version of former effect. The point is that by using the polynomials, one can easily find the turning point of the growth rate. For instance, based on the second column of the population growth table, the minimum after 0 is 0.22272. This indicates that for a city located at a distance of 222.72 km from the nearest

[21] In the regression, dist_big represents cities' distances to the nearest moderately large city in 2000, in 1000km. In reported tables, it is $dist(m)$, where m stands for moderately large.

[22] Controls include city-level GDP, population, economic density, population density, government spending, and investment from 1990, as well as distances to coastlines (Chen et al., 2014).

moderately large city, it experiences the peak of agglomeration shadow effect.

I plot the population growth rate against the distances with the third-order fitted line[23], shown in Figure 3. Additionally, I conduct a kernel regression and plot the non-parametric fitted line, displayed in Figure 4.

When plotting the growth rate of population against distances, the pattern reveals an initial decrease, followed by a flat range, and subsequently, an increase. Following the declining interval, cities located farther away from major centers exhibit accelerated growth, or at least a lower rate of decline.

Table 10: Regressions of Distances to Moderately Large Cities, Population Growth

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth
$dist(m)$	-0.0220**	-0.0120
	(0.0094)	(0.0098)
$dist(m)^2$	0.0378***	0.0240*
	(0.0121)	(0.0129)
$dist(m)^3$	-0.0118***	-0.0088**
	(0.0039)	(0.0042)
Constant	0.0103***	0.0081
	(0.0022)	(0.0146)
Observations	291	250
R-squared	0.494	0.649
Province FE	YES	YES
Controls	NO	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[23] Note that this fitted line does not include control variables, so it may not be identical to the polynomials implied by the former regressions.

Table 11: Regressions of Distances to Moderately Large Cities, GDP Growth

VARIABLES	(1) GDP Growth	(2) Small Subsample: GDP Growth
$dist(m)$	-0.0535**	-0.0028
	(0.0261)	(0.0263)
$dist(m)^2$	0.0716**	-0.0109
	(0.0336)	(0.0349)
$dist(m)^3$	-0.0184*	0.0080
	(0.0109)	(0.0114)
Constant	0.1298***	0.2453***
	(0.0062)	(0.0393)
Observations	291	250
R-squared	0.303	0.505
Province FE	YES	YES
Controls	NO	YES

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 3: Third Order Polynomial from Distance Regression

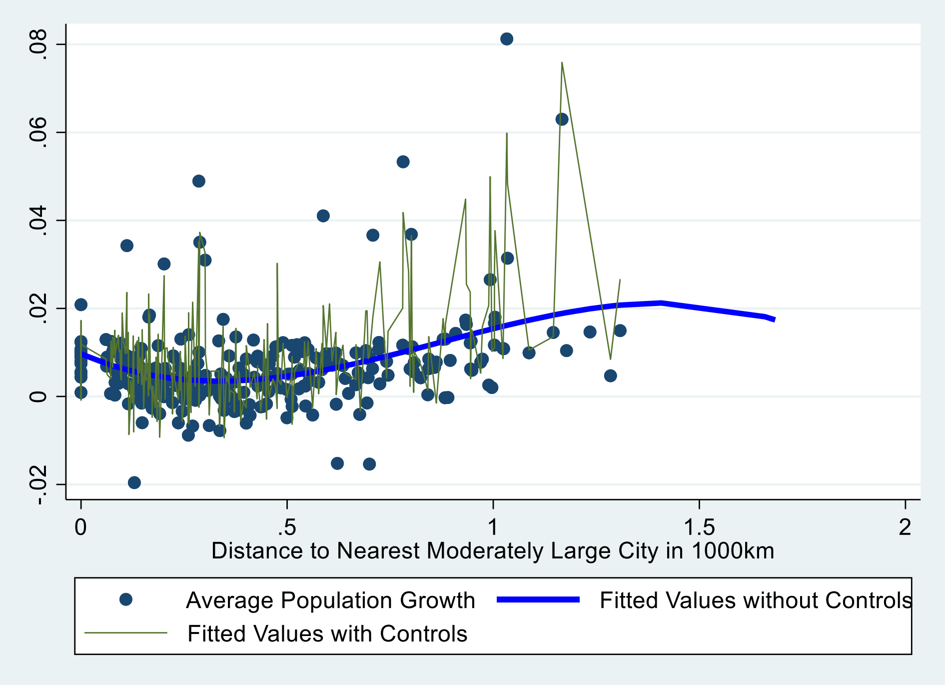
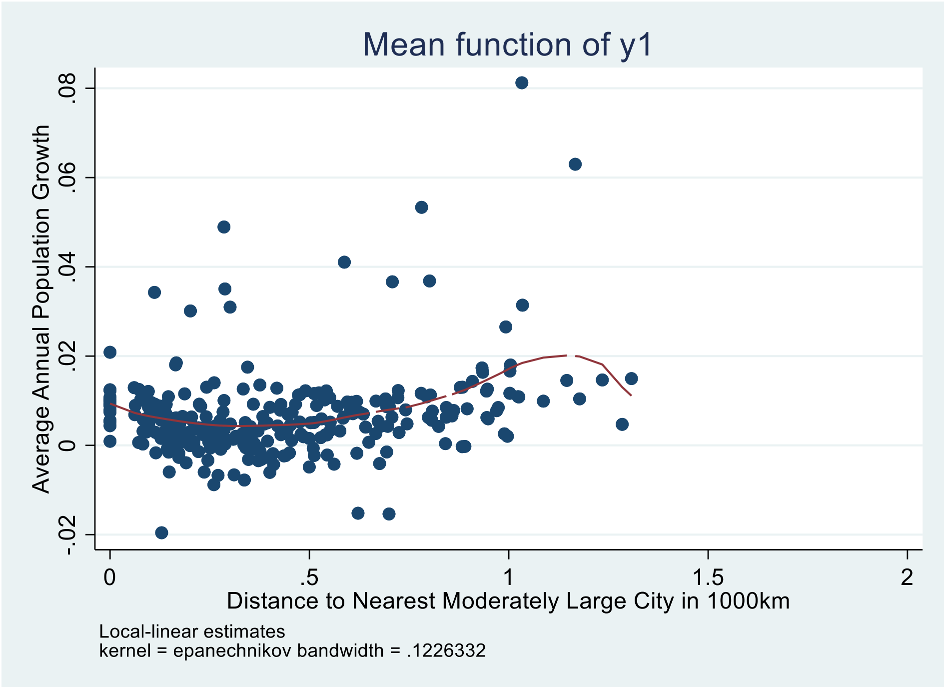


Figure 4: Kernal Regression on Distances



Essentially, baseline regressions are discrete versions of the distance regressions mentioned above: they regress growth rates against dummy variables indicating the existence of the nearest moderately large cities in corresponding intervals, while the distance regressions directly use continuous distances as explanatory variables[24]. From the baseline regression, I obtain six coefficients for six intervals. This allows the point estimates and their confidence intervals to be plotted. The comparison of the two sets of regressions is shown in Figures 5 and 6[25]. From the left graph, it can be observed that compared to the average growth rate of cities with their nearest large neighbor beyond 300km, those having a large neighbor within the 150-200km and 200-250km intervals have the lowest growth rate. This is generally consistent with the results from the distance regression.

[24] Another way to interpret this is that distance regressions represent a nonparametric version of baseline regressions.

[25] Since the distance regressions used for plotting do not include control variables, I have also excluded controls for the baseline regression used in this graph.

Figure 5: Comparison Between Two Regressions: Baseline Regression

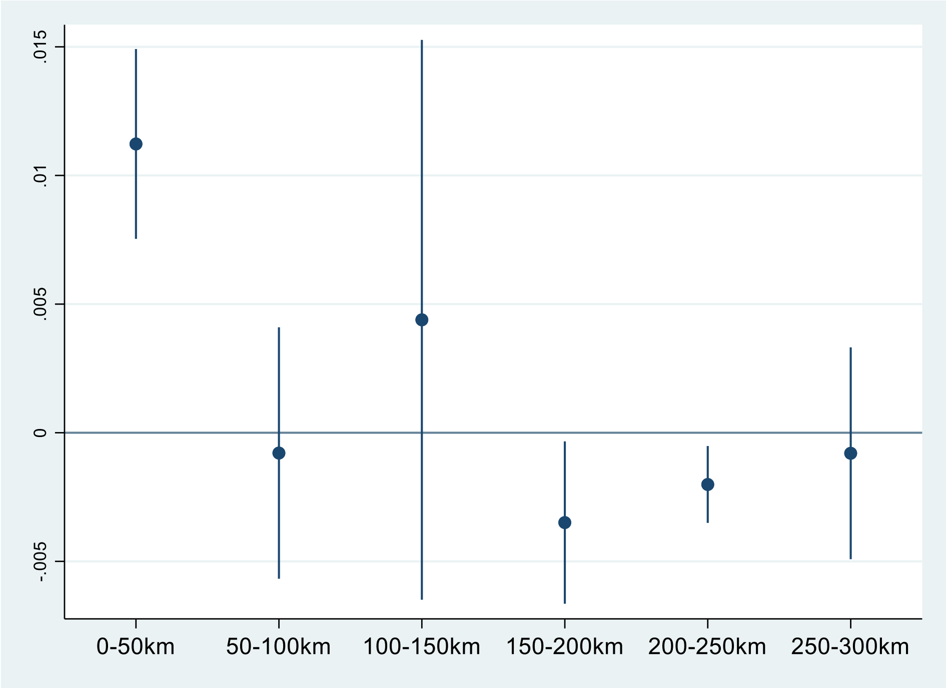
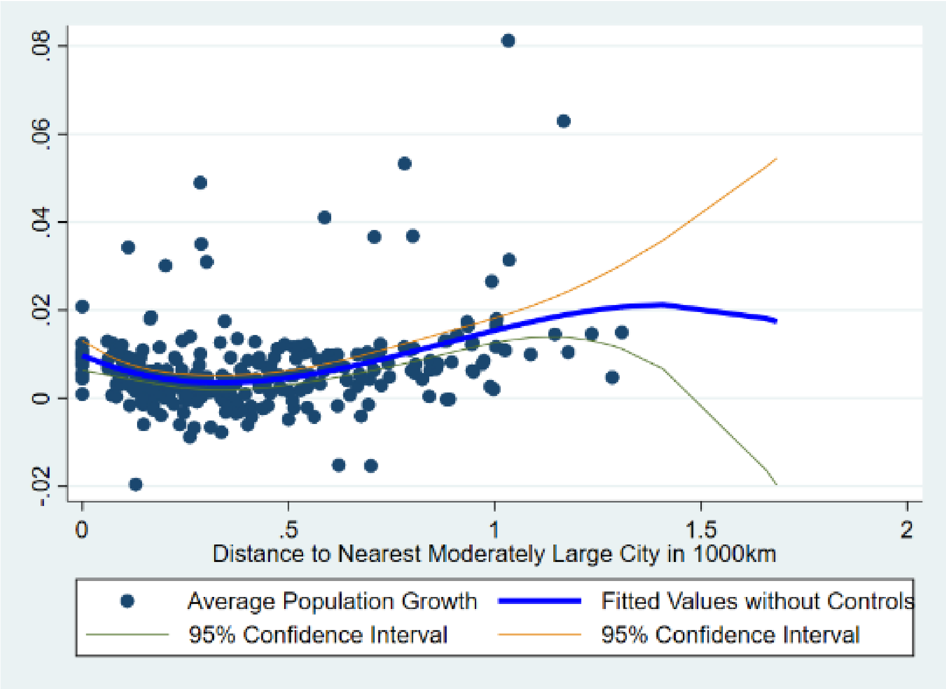


Figure 6: Comparison Between Two Regressions: Distance Regression



4.3 Political Hierarchy of Urban System in Mainland China

Concerning interregional dynamics in China, building on the previous discussion, there may be additional factors at play, specifically local protectionism and deprivation effects.

Historically, China initiated market reforms in the 1980s, with the pace of these reforms varying across regions. Young (2000) suggests that partial reform can introduce distortions, prompting local governments to establish various barriers to inter-city trade and factor movements. Local protectionism, as documented by Poncet (2003) at the provincial level and observed by Lu and Tao (2009) at the firm level, involves measures taken by local governments to shield local enterprises. In the context of this paper, it is possible that a large city has heterogeneous effects on its surrounding city neighbors based on whether these neighbors are in the same province. If a city benefits from being close to a large neighbor in the same province, there exists local protection.

Ades and Glaeser (1995) argue that political factors play a crucial role in determining the spatial allocation of resources. In China's hierarchical political system, characterized by a "top-down" pattern, urban centers, which typically administers surrounding locations (prefectures), may allocate more resources to city centers at the expense of peripheral areas. Fang and Liu (2007) highlight how large central cities in China engage in anti-market behaviors to enforce this "spatial deprivation".

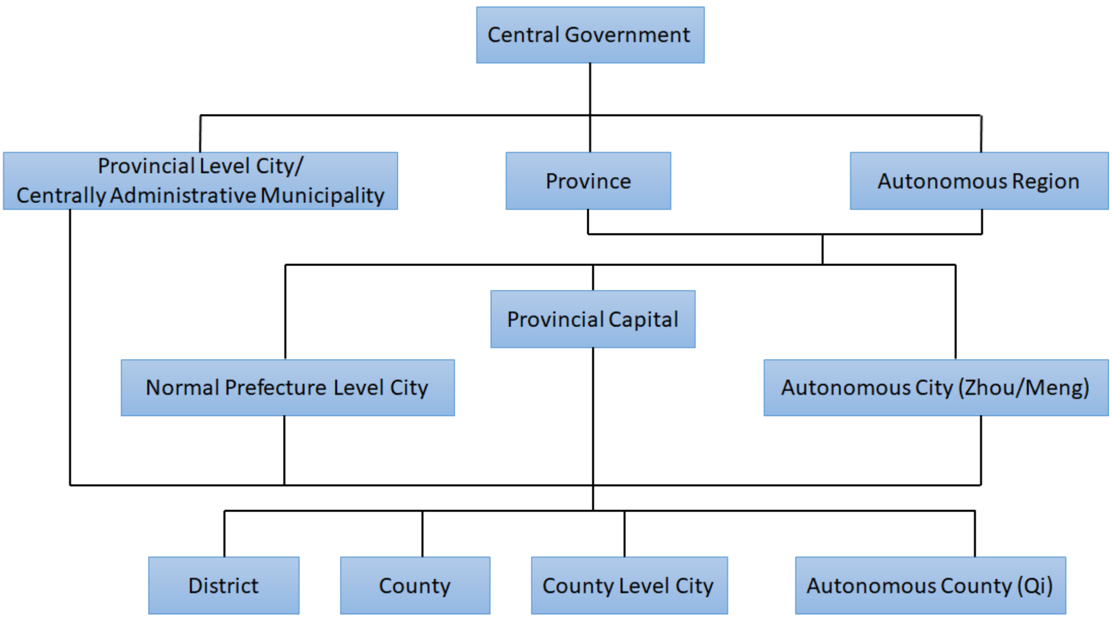
The political hierarchy of urban system in mainland China is sketched in Figure 7. Centrally administered municipalities [26] have the same political status as provinces, which is

[26] A direct-administered municipality (Zhíxiáshì; 'direct-administered city'; commonly known as municipality) is the Chinese city that is directly affiliated with the central government, instead of being placed under any provinces. There are four municipalities in China: Beijing, Tianjin, Shanghai, and Chongqing.

higher than that of normal prefecture cities. Additionally, provincial capitals are treated differently from a political standpoint, not only by their respective provinces but also by the central government. Thus, both centrally administered municipalities and provincial capitals could be viewed as "politically special."

When the central government makes decisions on policies regarding regional development and resource allocation, provincial-level governments (including centrally administered municipalities' governments) have a greater opportunity to be involved compared to prefecture-level cities. Similarly, when provincial governments make decisions on resource allocation among different local cities, provincial capitals are given similar priority. Therefore, this urban political hierarchy may serve as a driving force behind growth shadows, which is "spatial deprivation" mentioned above.

Figure 7: Political Hierarchy of Urban System in Mainland China



Building on the baseline regressions, it is straightforward to incorporate dummy variables reflecting the political relationship between cities and their large neighbors:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + CAM_i^L + CAP_i^L + Prov\_Cap_i^L + \epsilon_{\mathrm{i}} ,$$

where $I_{\mathrm{i}}^{\mathrm{DL}}$ are the same key variables as those in the baseline regressions in section 2; $CAM_i^L = 1,$ if any of this city's large neighbor over level L within the distance of 300km, is a centrally administered municipality (CAM); $CAP_i^L = 1,$ if any of city i's large neighbor over level L within the distance of 300km, is a provincial capital; $Prov\_Cap_i^L = 1,$ if any of city i's large neighbor over level L within the distance of 300km, is located in the same province as city i, and simultaneously serving as provincial capital. If any of these newly added dummy variables is negative, it indicates the presence of "spatial deprivation" for that type of politically special cities.

The results of this extension are presented in Table 12 for moderately large cities[27]. For the moderately large cities that are CAPs, the growth of surrounding cities in the same province is adversely impacted. Evidently, these large cities leverage their political advantages, which stem from their higher position in the political hierarchy. They may withhold essential resources required for growth from their surrounding areas. Interestingly, according to the third and fourth columns for CAM and CAP, some of them have positive spillovers. However, the combined coefficients are negative, meaning that the total effect of being close to the capital

[27] I do not report the results for very large cities because many of the newly added dummy variables are omitted in the regressions.

in the same province is negative. This result is logical: provincial capitals can only leverage their political status within their provinces.

To determine if this urban political hierarchy is the driving force behind growth shadows, it is also necessary to examine the presence of politically special cities within each defined distance interval. Specifically, the previous regression explored the effects of the presence of politically special cities within 300 km. To further analyze this, the following regression is conducted:

$$g_{\mathrm{i}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{base\ D}}^{L} I_{\mathrm{i}}^{\mathrm{DL}} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{CAM\ D}}^{L} CAM_{i}^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{CAP\ D}}^{L} CAP_{i}^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{PCAP\ D}}^{L} Prov\_Cap_{i}^{L} + \epsilon_{\mathrm{i}}\ ,$$

where $I_{\mathrm{i}}^{\mathrm{DL}}$ are the same key variables as those in the baseline regressions in section 2; $CAM_i^{DL} = 1$, if any of this city's large neighbor over level L within the distance interval D, is a centrally administered municipality (CAM); $CAP_i^L = 1$, if any of city i's large neighbor over level L within the distance interval D, is a provincial capital; $Prov\_Cap_i^L = 1$, if any of city i's large neighbor over level L within the distance interval D, is located in the same province as city i, and simultaneously serving as provincial capital. If any of these newly added dummy variables is negative, it indicates the presence of "spatial deprivation" for that type of politically special cities within the distance interval D.

The results are reported in the Table 13. For CAMs, their effects are staggered: positive in some intervals and negative in others. For provincial capitals, it can be observed that they cast urban growth shadows on surrounding cities within the same provinces, mostly in the 100-150 km and 250-300 km distances.

In both undecomposed and decomposed regressions, in the first two columns without fixed effects and controls, it can be observed that the baseline set of dummy variables (indicating the presence of the closest large neighbor within certain distances) become less significant and smaller in magnitude. This to some extent shows that urban growth shadows are driven by this political hierarchy of cities.

The direction to investigate further is to explore the channels of this spatial deprivation effect. Possible channels include transfer payments, taxes, government expenditure plans, and more. Another direction for further exploration involves delving into each city prefecture at a finer level[28]: within prefecture cities, are central districts or counties exerting spatial deprivation?

[28] This requires data at county level.

Table 12: Cross-Sectional Regressions with Political Hierarchy, Moderately Large Cities

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth	(3) Population Growth	(4) Small Subsample: Population Growth
$I(m, 50km)$	-	-	-	-
$I(m, 100km)$	0.0010	0.0017	-0.0008	-0.0020
	(0.0019)	(0.0022)	(0.0014)	(0.0033)
$I(m, 150km)$	-0.0021	-0.0043*	-0.0034*	-0.0058*
	(0.0020)	(0.0024)	(0.0018)	(0.0032)
$I(m, 200km)$	-0.0022	-0.0023	-0.0026*	-0.0039*
	(0.0019)	(0.0022)	(0.0015)	(0.0022)
$I(m, 250km)$	-0.0009	-0.0021	-0.0011	-0.0038**
	(0.0022)	(0.0026)	(0.0014)	(0.0018)
$I(m, 300km)$	-0.0020	-0.0028	-0.0017	-0.0038**
	(0.0021)	(0.0021)	(0.0013)	(0.0015)
$CAM(m)$	0.0030**	0.0025**	0.0006	0.0051***
	(0.0012)	(0.0012)	(0.0024)	(0.0016)
$CAP(m)$	0.0001	0.0012	0.0030*	0.0039**
	(0.0016)	(0.0020)	(0.0015)	(0.0014)
$Prov\_CAP(m)$	-0.0055*	-0.0082***	-0.0054*	-0.0044*
	(0.0028)	(0.0017)	(0.0029)	(0.0023)
Constant	0.0076***	0.0076***	-0.6815	-0.8306
	(0.0016)	(0.0018)	(0.8720)	(0.9708)
Observations	289	235	245	199
R-squared	0.032	0.047	0.340	0.386
Geographic Control	YES	YES	YES	YES
Province FE	NO	NO	YES	YES
Economic Control	NO	NO	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Cross-Sectional Regressions with Political Hierarchy, Moderately Large Cities, Decomposed into Different Distance Intervals

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth	(3) Population Growth	(4) Small Subsample: Population Growth
$I(m, 50km)$	-	-	-	-
$I(m, 100km)$	0.0008	0.0007	-0.0014	-0.0030
	(0.0020)	(0.0023)	(0.0021)	(0.0042)
$I(m, 150km)$	-0.0021	-0.0026	-0.0028*	-0.0043
	(0.0018)	(0.0021)	(0.0015)	(0.0035)
$I(m, 200km)$	-0.0035*	-0.0031	-0.0040**	-0.0047**
	(0.0018)	(0.0019)	(0.0015)	(0.0020)
$I(m, 250km)$	0.0000	-0.0020	-0.0013	-0.0047***
	(0.0025)	(0.0031)	(0.0020)	(0.0016)
$I(m, 300km)$	-0.0019	-0.0025	-0.0019	-0.0036**
	(0.0022)	(0.0023)	(0.0014)	(0.0016)
$CAP(m, 50km)$	-	-	-	-
$CAP(m, 100km)$	-0.0011		0.0054	0.0189***
	(0.0099)		(0.0075)	(0.0018)
$CAP(m, 150km)$	-0.0037***	-0.0029***	-0.0030**	-0.0022
	(0.0010)	(0.0010)	(0.0012)	(0.0021)
$CAP(m, 200km)$	0.0011	-0.0007	0.0011	-0.0012
	(0.0012)	(0.0016)	(0.0018)	(0.0020)
$CAP(m, 250km)$	-0.0001	0.0005	0.0000	0.0019
	(0.0026)	(0.0025)	(0.0014)	(0.0015)
$CAP(m, 300km)$	0.0004	0.0012	0.0035**	0.0039**
	(0.0026)	(0.0029)	(0.0014)	(0.0016)
$CAM(m, 50km)$	-	-	-	-
$CAM(m, 100km)$	0.0068**	0.0160***	0.0062***	0.0108***
	(0.0029)	(0.0047)	(0.0019)	(0.0034)
$CAM(m, 150km)$	0.0030		0.0000	
	(0.0030)		(0.0025)	
$CAM(m, 200km)$	0.0027	-0.0028	-0.0005	-0.0036**
	(0.0037)	(0.0018)	(0.0019)	(0.0017)
$CAM(m, 250km)$	-0.0071***	-0.0049**	-0.0167***	-0.0128***
	(0.0016)	(0.0018)	(0.0023)	(0.0020)
$CAM(m, 300km)$	0.0066***	0.0062***	0.0144***	0.0154***
	(0.0011)	(0.0012)	(0.0010)	(0.0014)
$Prov\_CAP(m, 50km)$	-	-	-	-

$Prov\_CAP(m, 100km)$	-		-	-
$Prov\_CAP(m, 150km)$	-0.0014	-0.0179***	-0.0047	-0.0180***
	(0.0076)	(0.0008)	(0.0074)	(0.0005)
$Prov\_CAP(m, 200km)$	0.0056	0.0033	-0.0031	-0.0044**
	(0.0045)	(0.0032)	(0.0021)	(0.0016)
$Prov\_CAP(m, 250km)$	-0.0009	0.0030	0.0039*	0.0057***
	(0.0030)	(0.0025)	(0.0021)	(0.0014)
$Prov\_CAP(m, 300km)$	-0.0078**	-0.0111***	-0.0064***	-0.0070***
	(0.0036)	(0.0039)	(0.0022)	(0.0013)
Constant	0.0076***	0.0076***	-0.7415	-1.0791
	(0.0016)	(0.0019)	(0.8677)	(0.9737)
Observations	289	235	245	199
R-squared	0.040	0.065	0.352	0.407
Geographic Control	YES	YES	YES	YES
Province FE	NO	NO	YES	YES
Economic Control	NO	NO	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Robustness

5.1 Panel Version of Baseline Regressions

For time varying dummy variables $I_{\mathrm{it}}^{\mathrm{DL}}$, I regress city growth rate on them:

$$g_{\mathrm{it}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}} \,,$$

where i denotes a location, t represents year, and β_{D}^{L} are coefficients of interest; ω_{i} and τ_{t} are city and time fixed effects. Regressions are conducted separately for moderately large cities and very large cities, reported in Tables 14 and 15. The patterns are similar to those of the baseline regression: urban agglomeration shadows exist, and very large cities cast shadows further and to a greater extent.

It should be noted that panel regressions are limited. For example, a city that consistently appears in the large city lists each year would not reveal the spillover effects experienced by its neighbors in the previous regressions, as fixed effects would absorb these effects. From an econometric perspective, adding fixed effects to the panel regression would restrict our analysis to the effects experienced by cities near the "new entrants" or "switchers" to the large city lists[29]. They provide insights into the growth shadows of cities that switch into the top 1 or 5% relative to those that switch out of the top 1 or 5%.

[29] According to the data, transitions for large cities exist. For instance, only two cities have always been very large cities over 20 years: Shanghai and Chongqing. In some years, Chengdu and Beijing switched in relative ranking.

I also add controls to the panel regressions:

$$g_{\mathrm{it}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{1}\,\mathbf{it}}\delta + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}}\,,$$

where $X_{1\mathrm{i}}$ is a vector of control variables. These controls are time-invariant and are drawn from 1990 city statistics, instead of statistics after 2000, to mitigate endogeneity. They include city-level GDP, population, economic density, population density, FDI amount, proportion of population with above high school education, government spending, and investment. I incorporate them into the panel regressions, by interacting them with year dummies. Additionally, I include the lags of dependent variables in the controls[30]. The results are reported in Table 16 and Table 17 for very large cities and moderately large cities respectively: growth shadows still exist within 200km.

[30] After lag order selection, the optimal lag for population growth rates is 2, and for GDP growth, it is 5.

Table 14: Baseline Regressions for Very Large Cities, Robustness Check by using Panel Regressions

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth	(3) GDP Growth	(4) Small Subsample: GDP Growth
$I(v, 50km)$	-0.1725***		-0.0518***	
	(0.0016)		(0.0119)	
$I(v, 100km)$	-0.1311***	-0.0008	-0.0079*	0.0162***
	(0.0012)	(0.0012)	(0.0046)	(0.0046)
$I(v, 150km)$	-0.0080***	-0.0034*	0.0164***	0.0261***
	(0.0013)	(0.0018)	(0.0045)	(0.0046)
$I(v, 200km)$	-0.0044***	-0.0045***	0.0404***	0.0490***
	(0.0013)	(0.0013)	(0.0076)	(0.0059)
$I(v, 250km)$	0.0007	0.0019	0.0284***	0.0327***
	(0.0017)	(0.0014)	(0.0048)	(0.0056)
$I(v, 300km)$	-0.0033**	-0.0035**	0.0118	0.0159*
	(0.0012)	(0.0016)	(0.0078)	(0.0080)
Constant	0.0102***	0.0076***	0.1317***	0.1317***
	(0.0001)	(0.0001)	(0.0007)	(0.0004)
Observations	5,037	4,010	5,037	4,010
R-squared	0.078	0.088	0.346	0.343

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city and year fixed effects.

Table 15: Baseline Regressions for Very Moderately Large Cities, Robustness Check by using Panel Regressions

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth	(3) GDP Growth	(4) Small Subsample: GDP Growth
$I(m, 50km)$	-	-	-	-
$I(m, 100km)$	-0.0054*	-0.0008	-0.0370*	-0.0399*
	(0.0031)	(0.0025)	(0.0188)	(0.0207)
$I(m, 150km)$	-0.0053*	-0.0007	-0.0078	-0.0328
	(0.0030)	(0.0029)	(0.0204)	(0.0256)
$I(m, 200km)$	-0.0016	0.0037	-0.0088	-0.0051
	(0.0020)	(0.0034)	(0.0151)	(0.0195)
$I(m, 250km)$	0.0021	0.0027	-0.0069	-0.0087
	(0.0040)	(0.0044)	(0.0210)	(0.0283)
$I(m, 300km)$	-0.0112	-0.0031	-0.0205	-0.0281
	(0.0077)	(0.0024)	(0.0215)	(0.0237)
Constant	0.0097***	0.0069***	0.1389***	0.1404***
	(0.0010)	(0.0010)	(0.0065)	(0.0072)
Observations	5,037	4,014	5,037	4,014
R-squared	0.064	0.095	0.345	0.347

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city and year fixed effects.

Table 16: Baseline Regressions for Very Large Cities, Robustness Check by using Panel Regressions and Adding Controls

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(v, 50km)$	-0.4317***	-0.0799***
	(0.0615)	(0.0072)
$I(v, 100km)$	-0.1471***	-0.0473***
	(0.0117)	(0.0060)
$I(v, 150km)$	-0.0065***	0.0183***
	(0.0022)	(0.0054)
$I(v, 200km)$	-0.0033**	0.0345***
	(0.0013)	(0.0075)
$I(v, 250km)$	-0.0016	0.0472***
	(0.0016)	(0.0057)
$I(v, 300km)$	-0.0026	0.0237**
	(0.0028)	(0.0099)
Constant	0.0176***	0.0972***
	(0.0027)	(0.0084)
Observations	3,856	3,856
R-squared	0.174	0.539

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city fixed effects, year fixed effects, lags and interacted controls.

Table 17: Baseline Regressions for Moderately Large Cities, Robustness Check by using Panel Regressions

	(1)	(2)
VARIABLES	Population Growth	GDP Growth
$I(m, 50km)$	-	-
$I(m, 100km)$	-0.0072**	-0.0468**
	(0.0033)	(0.0210)
$I(m, 150km)$	-0.0034	-0.0217
	(0.0031)	(0.0177)
$I(m, 200km)$	-0.0006	-0.0183
	(0.0030)	(0.0152)
$I(m, 250km)$	0.0082	-0.0220
	(0.0055)	(0.0189)
$I(m, 300km)$	-0.0125	-0.0296*
	(0.0115)	(0.0173)
Constant	0.0158***	0.1269***
	(0.0027)	(0.0209)
Observations	3,856	3,856
R-squared	0.153	0.491

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city fixed effects, year fixed effects, lags and interacted controls.

5.2 Panel Regressions for High-Speed Railway

I continue to use the same instruments as before, which are time-invariant variables. Following Dong et al. (2021), I interact these instruments with time-varying information, specifically the countrys overall GDP, to make the instrument time-varying. Thus, the first stage is:

$$I_{\mathrm{i}}^{\mathrm{DL}} HSR_{it}^{DL} = \sum_{D=[0km,50km]}^{[250km,300km]} \mu_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}}\, Rail1962_{it}^{DL} + \sum_{D=[0km,50km]}^{[250km,300km]} \varphi_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + HSR_{it} + \boldsymbol{X}_{\mathbf{2\ it}}\delta + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}} ,$$

where $Rail1962_{it}^{DL} = Rail1962_{i}^{DL} * CountryGDP_{t}$

The second stage follows as[31]:

$$g_{\mathrm{it}} = \sum_{D=[0km,50km]}^{[250km,300km]} \alpha_{\mathrm{D}}^{L}\, (\widehat{I_{\mathrm{it}}^{\mathrm{DL}} HSR_{it}^{DL}}) + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{2\ it}}\delta + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}} ,$$

The results for very large cities are reported in Table 18. The patterns of coefficients for key variables closely resemble those observed in the cross-sectional regressions.

I also employ another proxy for HSR connection. Following Dong et al. (2021), I construct a Market Access (MA) variable[32] that captures the time-varying information on the

[31] Observations used are identical to the HSR section, starting at 2008.

[32] For a detailed description of the construction of Market Access (MA) variables, please refer to Appendix 3.

construction of high-speed railway over time. Generally speaking, this Market Access (MA) variable reflects the level of connectivity of a location to other locations[33]. The following regression is conducted:

$$g_{\mathrm{it}} = \sum_{D=[0km,50km]}^{[250km,300km]} \alpha_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} MA_{it} + \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + \boldsymbol{X}_{\mathbf{4\ it}}\delta + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}}\,,$$

where $\boldsymbol{X}_{\mathbf{4\ it}}$ is a vector of control variables containing MA_{it} itself. The results are present in Table 19[34].

The interaction terms within 200 km are positive. This aligns with the previous results: improved connectivity by HSR tends to alleviate agglomeration shadow effects.

Further exploration could involve addressing the endogeneity of market access, possibly by employing self-excluded market access (Lin, 2017) or instrumental variables (Dong et al., 2021).

[33] Donaldson and Hornbeck (2016) propose a reduced form market access implied by general equilibrium trade theory between locations, which is isomorphic to the market potential.

[34] In the table, variable MA stands for Market Access Indicator..

Table 18: HSR Panel Regressions for Very Large Cities, IV 2nd stage

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(v, 50km)$	-0.1902***	-0.0247**
	(0.0080)	(0.0103)
$I(v, 100km)$	-0.1453***	0.0147***
	(0.0063)	(0.0052)
$I(v, 150km)$	-0.0087***	0.0191**
	(0.0030)	(0.0077)
$I(v, 200km)$	-0.0050***	0.0364***
	(0.0016)	(0.0074)
$I(v, 250km)$	0.0005	0.0328***
	(0.0022)	(0.0046)
$I(v, 300km)$	-0.0037*	0.0056
	(0.0018)	(0.0074)
$HSR(v, 100km)$	0.0320*	0.0494***
	(0.0177)	(0.0105)
$HSR(v, 150km)$	-0.0020	-0.0270
	(0.0051)	(0.0186)
$HSR(v, 200km)$	0.0017*	0.0354**
	(0.0009)	(0.0164)
$HSR(v, 250km)$	0.0003	-0.0454***
	(0.0022)	(0.0110)
$HSR(v, 300km)$	0.0021	0.0284**
	(0.0041)	(0.0124)
HSR	0.0004	0.0059
	(0.0029)	(0.0074)
Constant	0.0101***	0.1306***
	(0.0006)	(0.0016)
Observations	5,037	5,037

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city and year fixed effects.

Table 19: HSR Panel Regressions for Very Large Cities, using Market Access

VARIABLES	(1) Population Growth	(2) GDP Growth
$I(v, 50km)$	-0.3300***	-0.8188***
	(0.0115)	(0.1006)
$I(v, 100km)$	-0.0354**	0.0230
	(0.0151)	(0.0411)
$I(v, 150km)$	-0.0228**	-0.0586
	(0.0100)	(0.0711)
$I(v, 200km)$	-0.0188***	-0.0971**
	(0.0057)	(0.0405)
$I(v, 250km)$	-0.0053	0.0826*
	(0.0098)	(0.0450)
$I(v, 300km)$	-0.0042	-0.0798
	(0.0120)	(0.0527)
$I(v, 50km) * MA$	0.0285***	0.0674***
	(0.0009)	(0.0086)
$I(v, 100km) * MA$	0.0034**	-0.0020
	(0.0014)	(0.0041)
$I(v, 150km) * MA$	0.0025**	0.0093
	(0.0011)	(0.0081)
$I(v, 200km) * MA$	0.0017**	0.0166***
	(0.0008)	(0.0057)
$I(v, 250km) * MA$	0.0004	-0.0079
	(0.0012)	(0.0060)
$I(v, 300km) * MA$	0.0000	0.0132*
	(0.0015)	(0.0070)
MA	0.0002	0.0076*
	(0.0016)	(0.0039)
Constant	0.0060	0.0669**
	(0.0106)	(0.0263)
Observations	2,858	2,858
R-squared	0.122	0.554

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city and year fixed effects.

5.3 Panel Regressions for Urban Political Hierarchy Part

With panel data, the following regression is conducted:

$$g_{\mathrm{it}} = \sum_{D=[0km,50km]}^{[250km,300km]} \beta_{\mathrm{D}}^{L} I_{\mathrm{it}}^{\mathrm{DL}} + CAM_{it}^{L} + CAP_{it}^{L} + Prov\_Cap_{it}^{L} + \omega_{\mathrm{i}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{it}} \,,$$

where $I_{\mathrm{it}}^{\mathrm{DL}}$ are the same key variables as those in the baseline regressions in chapter 2; $CAM_{it}^{L} = 1,$ if any of this city's large neighbor over level L within the distance of 300km, is a centrally administered municipality (CAM) in year $t-1$; $CAP_{it}^{L} = 1,$ if any of city i's large neighbor over level L within the distance of 300km, is a provincial capital in year $t-1$;. $Prov\_Cap_{it}^{L} = 1,$ if any of city i's large neighbor over level L within the distance of 300km, is located in the same province as city i in year $t-1$ and serving as a provincial capital.

The results of this robustness check are presented in the Table 20. The main driving force of growth shadows is still provincial capitals in the same province.

Table 20: Panel Regressions with Political Hierarchy, Moderately Large Cities

VARIABLES	(1) Population Growth	(2) Small Subsample: Population Growth
$I(m, 50km)$	-	-
$I(m, 100km)$	-0.0102**	-0.0086**
	(0.0048)	(0.0038)
$I(m, 150km)$	-0.0082*	-0.0054*
	(0.0043)	(0.0031)
$I(m, 200km)$	-0.0029	0.0039
	(0.0023)	(0.0032)
$I(m, 250km)$	0.0007	0.0012
	(0.0048)	(0.0045)
$I(m, 300km)$	-0.0140	-0.0065**
	(0.0087)	(0.0025)
$CAM(m)$	0.0021	-0.0028
	(0.0021)	(0.0020)
$CAP(m)$	0.0451	0.0473
	(0.0317)	(0.0345)
$Prov\_CAP(m)$	-0.0673**	-0.0620**
	(0.0276)	(0.0283)
Constant	0.0094***	0.0065***
	(0.0008)	(0.0009)
Observations	5,037	4,014
R-squared	0.488	0.590

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: all columns include city and year fixed effects.

6. Conclusion

This study investigates the impact of proximity to large cities on the growth of surrounding areas in mainland China over the past two decades. The findings reveal that mega-cities consistently posed challenges to the population growth of cities within at least 150-kilometer radius, demonstrating the existence of agglomeration shadow effects. This effect persists across various time frames and subsamples, with different sizes of large center cities affecting the coverage of shadow effects. The analysis delves into the mechanisms through which large cities impact surrounding areas, by considering such factors as transportation networks, geographical distances, and the urban political hierarchy within China.

A reduction in inter-city travel costs emerges as a mitigating factor against the agglomeration shadow effect, while a decrease in intra-city commuting costs in central cities appears to exacerbate it. Cities connected to their large neighbor within 250 km by High-Speed Railway (HSR) experience fewer negative effects in terms of population growth. When a large city has ring roads, it tends to cast more agglomeration shadows on the surrounding areas. Geographical distances to large cities are also found to influence city growth rates, with an initial decline, followed by stagnation, and subsequent acceleration for cities farther away from major centers.

The study considers the urban political hierarchy in China, identifying local deprivation effects as potential additional factors. Large cities, with their higher position in the political hierarchy, are found to impact negatively the growth of their neighbors, especially if they were provincial capitals located in the same province. This suggests that major city centers use their political advantages to withhold essential resources, exerting a deprivation effect on surrounding areas.

In conclusion, this research contributes insights into the complex dynamics of urban growth in mainland China, by shedding light on the interplay of geographical, infrastructural, and political factors. The findings have implications for urban planning and policy formulation, emphasizing the need for a comprehensive understanding of these dynamics in fostering balanced and sustainable development across regions.

Appendix 1: Supplementary Tables

Table A1: Summary Statistics

Variable	Mean	SD	Min	p50	Max
pop_growth	0.0066	0.0093	-0.0146	0.0059	0.0334
GDP_growth	0.0841	0.0778	-0.0396	0.0782	0.2981
very _50km	0.0004	0.0199	0.0000	0.0000	1.0000
very _100km	0.0093	0.0961	0.0000	0.0000	1.0000
very_150km	0.0270	0.1620	0.0000	0.0000	1.0000
very_200km	0.0305	0.1721	0.0000	0.0000	1.0000
very_250km	0.0236	0.1518	0.0000	0.0000	1.0000
very_300km	0.0329	0.1784	0.0000	0.0000	1.0000
moderately_50km	0.0000	0.0000	0.0000	0.0000	0.0000
moderately_100km	0.0321	0.1763	0.0000	0.0000	1.0000
moderately_150km	0.0866	0.2813	0.0000	0.0000	1.0000
moderately_200km	0.0884	0.2839	0.0000	0.0000	1.0000
moderately_250km	0.0884	0.2839	0.0000	0.0000	1.0000
moderately_300km	0.0642	0.2452	0.0000	0.0000	1.0000
HSR	0.1858	0.3890	0.0000	0.0000	1.0000

Observation: 5037.

Table A2: Summary Statistics for Control Variables

Variable	Mean	SD	Min	p50	Max
density_90	0.0317	0.0399	0.0002	0.0203	0.4346
density2_90	0.0026	0.0125	0.0000	0.0004	0.1889
ln_GDP_90	12.5658	1.1353	10.1887	12.7127	15.8233
ln_pop_90	5.0743	1.0839	2.3214	5.1003	7.3023
inv_90	0.1822	0.1279	0.0341	0.1453	0.8664
FDI_90	0.0017	0.0048	0.0000	0.0002	0.0400
gov_90	0.0906	0.0305	0.0104	0.0864	0.1855

Table A3: Share of Cities with Large Neighbors, Panel

Size_distance	Share		Size_distance	Share	
	Separate	Accumulated		Separate	Accumulated
very _50km	0.0004	0.0004	moderately_50km	0.003569	0.003569
very _100km	0.0093	0.0097	moderately_100km	0.069191	0.07276
very_150km	0.027	0.0367	moderately_150km	0.094171	0.166931
very_200km	0.0305	0.0672	moderately_200km	0.089017	0.255948
very_250km	0.0236	0.0908	moderately_250km	0.101309	0.357256
very_300km	0.0329	0.1237	moderately_300km	0.056701	0.413957

Table A4: Share of Cities with Large Neighbors, 2000 Cross-Sectional

Size_distance	Panel Data Share		Size_distance	Panel Data Share	
	Separate	Accumulated		Separate	Accumulated
very _50km	0	0	moderately_50km	0	0
very _100km	0.013423	0.013423	moderately_100km	0.02349	0.02349
very_150km	0.033557	0.04698	moderately_150km	0.083893	0.107383
very_200km	0.033557	0.080537	moderately_200km	0.087248	0.194631
very_250km	0.026846	0.107382	moderately_250km	0.090604	0.285235
very_300km	0.040269	0.147651	moderately_300km	0.080537	0.365772

Appendix 2: Construction of Dummy Variables Indicating Proximity to Large Cities

After obtaining the population data and defining two levels of large cities, I obtained geographical information of cities from the National Earth System Science Data Center and imported all the above information into GIS. This allowed me to acquire the geographical location of each city in each year, with large cities identified by special marks.

I then used the "spatial join" function in GIS to create the initial dummy variables. For each distance of L and each level of d, I used spatial join to determine, for each city i in every year t, if there exists a centroid of a city with a population over L within a circle with a radius of d[35] centered at the centroid of city i. When there is at least one large city within the specified distance, the dummy variable takes the value of 1 (referred to as $I_{\mathrm{it}}^{\mathrm{dL}}$). Additionally, I kept track of the names of the large neighbors for each d, L, i, and t, which formed a list of large neighbors (referred to as $List_{\mathrm{it}}^{\mathrm{dL}}$).

Please note that these dummy variables $I_{\mathrm{it}}^{\mathrm{dL}}$ are different from the ones used in the baseline regression (referred to as $I_{\mathrm{it}}^{\mathrm{DL}}$), as the latter exclude large neighbors within a smaller distance bandwidth. To get $I_{\mathrm{it}}^{\mathrm{DL}}$, I impose:

$$I_{\mathrm{it}}^{\mathrm{DL}} = \begin{cases} 1 \ \ if\ d = upper\ bound\ of\ D = 50km\ \ and\ I_{\mathrm{it}}^{\mathrm{dL}} = 1 \\ 1 \ \ if\ d = upper\ bound\ of\ D \in \{100km, 150km, \\ \quad 200km, 250km, 300km\}\ and\ \left(\prod_{\tilde{d}=50km}^{(d-50km)} (1 - I_{\mathrm{it}}^{\tilde{d}\mathrm{L}})\right)\left(I_{\mathrm{it}}^{\mathrm{dL}}\right) = 1 \\ 0 \ \ otherwise \end{cases}$$

[35] d: {50km, 100km, 150km, 200km, 250km, 300km}. This is different from D, which is composed of intervals.

Also, to get $List_{\mathrm{it}}^{\mathrm{DL}}$[36], I impose the following:

$$List_{\mathrm{it}}^{\mathrm{DL}} = \begin{cases} List_{\mathrm{it}}^{\mathrm{dL}} & if\ d = upper\ bound\ of\ D = 50km \\ List_{\mathrm{it}}^{\mathrm{dL}} - List_{\mathrm{it}}^{\mathrm{d-50km\ L}} & if\ d = upper\ bound\ of\ D = \{100km, \\ & 150km, 200km, 250km, 300km\} \end{cases}$$

In this way, I get the vectors of dummy variables $I_{\mathrm{it}}^{\mathrm{DL}}$.

[36] This list is used in the HSR part of the paper, to match the large cities which have HSR.

Appendix 3: Construction of Market Access Variables

The market access variable is constructed following the approach of Lin (2017) and Dong et al. (2021). I obtained shapefiles containing the geographic information and shapes of high-speed rails in 2020, normal-speed rails in 2000, and normal-speed roads that connect cities with railways and directly connect cities. These files were imported into GIS, and the "network analysis" tool was used to determine the possible routes that take the least amount of time for each city pair. This provided the shortest travel time between each city in 2020.

Next, I obtained time-varying information on the construction of high-speed railways (HSR) from Gaotie.cn, which provides details on the construction time of each HSR station and each HSR segment line. Using this information, I edited the shapefile of the 2020 HSR to reflect the construction status for each earlier year. This process involved deleting the lines that had not been constructed at that time, allowing me to create an HSR shapefile for each year after 2007. Following the same steps as before, I calculated the shortest travel time between each city in each year.

It's important to note that this least travel time only captures the time-varying information in the HSR system, as the normal-speed railway system and road system are not adjusted for each year. Therefore, the market access variable based on this shortest travel time reflects only the change in the HSR system, not the change in other transportation networks.

The equation used to compute market access is as follows:

$$MA_{it} = \sum_{j=1, j \neq i}^{N} Income_{j,2000} \cdot e^{-\gamma d_{ijt}} \quad ,$$

where i refers to city itself and j refers to any other cities, γ is a parameter that captures spatial frictions between cities, and d_{ijt} is the travel time in minutes between city i and city j. Following Zheng and Kahn (2013), γ is set to be 0.02. To mitigate endogeneity issues, $Income_{j,2000}$ uses city-level GDP data from 2000.

The following figures show the rapid expansion of HSR system in mainland China.

Figure A1: High-Speed Railway Systems in Mainland China

Year 2010

Year 2013

Year 2016

Year 2019

Reference

Ades, A. F., & Glaeser, E. L. (1995). Trade and circuses: Explaining urban giants. *The quarterly journal of economics*, *110*(1), 195–227. Oxford University Press (OUP).

Allen, T., & Arkolakis, C. (2014). Trade and the topography of the spatial economy. *The quarterly journal of economics*, *129*(3), 1085–1140. Oxford Academic.

Au, C.-C., & Henderson, J. V. (2006). Are Chinese cities too small? *The Review of economic studies*, *73*(3), 549–576. Oxford Academic.

Asian Development Bank. (2002). Technical assistance to the PRC for the Hebei provincial development strategy.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., & Zhang, Q. (2017). Roads, railroads, and decentralization of Chinese cities. *The review of economics and statistics*, *99*(3), 435–448. MIT Press - Journals.

Baum-Snow, N., Henderson, J. V., Turner, M. A., Zhang, Q., & Brandt, L. (2020). Does investment in national highways help or hurt hinterland city growth? *Journal of urban economics*, *115*, 103124. Elsevier.

Behrens, K., Duranton, G., & Robert-Nicoud, F. (2014). Productive cities: Sorting, selection, and agglomeration. *The journal of political economy*, *122*(3), 507–553. The University of Chicago Press.

Black, D., & Henderson, V. (1999). Spatial evolution of population and industry in the United States. *The American economic review*, *89*(2), 321–327. pubs.aeaweb.org.

Bosker, M., & Buringh, E. (2017). City seeds: Geography and the origins of the European city system. *Journal of urban economics*, *98*, 139–157. Elsevier.

Brülhart, M., & Koenig, P. (2006). New economic geography meets Comecon. *Economics of transition*, *14*(2), 245–267. Wiley.

Caliendo, L., Parro, F., Rossi-Hansberg, E., & Sarte, P.-D. (2018). The impact of regional and sectoral productivity changes on the U.S. economy. *The Review of economic studies*, *85*(4), 2042–2096. Oxford University Press (OUP).

National Bureau of Statistics of China. (2020). *China urban statistical yearbook.* Retrieved from https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907995.html

Chan, K. W. (2019). China's hukou system at 60: Continuity and reform. *Handbook on urban* *development in China*, *59*. Edward Elgar Publishing Cheltenham. Retrieved from https://books.google.com/books?hl=en&lr=&id=FQyEDwAAQBAJ&oi=fnd&pg=PA59&dq=hukou+system&ots=-82DwxZaTL&sig=ZsOGcJNzH9ZZBRENes1hxiVKrcw

Chen, Z., Lu, M., & Xu, Z. (2011). A core-periphery model of urban economic growth: Empirical evidence using Chinese city-level data, 1990-2006. Citeseer. Retrieved from https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=26c228fc2d55beba6013d87bf5b714994b911422

Chen, Z., Lu, M., & Xu, Z. (n.d.). Agglomeration shadow. *hhs.se*. Retrieved from https://www.hhs.se/contentassets/c9558a10642a49d9815e5b09f189b9dc/agglomeration-shadow.pdf

Christaller, W. (1933). Die zentralen Orte in Süddeutschland (the central places in southern Germany). *Jena: Gustav Fischer*.

Combes, P.-P. (2000). Economic structure and local growth: France, 1984–1993. *Journal of urban economics*, *47*(3), 329–355. Elsevier.

Cronon, W. (2009). Nature's Metropolis: Chicago and the Great West. W. W. Norton & Company.

Cuberes, D., Desmet, K., & Rappaport, J. (2021). Urban growth shadows. *Journal of urban economics*, *123*, 103334. Elsevier.

Davis, D. R., & Weinstein, D. E. (2002). Bones, bombs, and break points: The geography of economic activity. *The American economic review*, *92*(5), 1269–1289. aeaweb.org.

Desmet, K., Nagy, D. K., & Rossi-Hansberg, E. (2018). The geography of development. *The journal of political economy*, *126*(3), 903–983. The University of Chicago Press.

Desmet, K., & Rossi-Hansberg, E. (2013). Urban accounting and welfare. *The American economic review*, *103*(6), 2296–2327. aeaweb.org.

Desmet, K., & Rossi-Hansberg, E. (2014). Spatial development. *The American economic review*, *104*(4), 1211–1243. aeaweb.org.

Desmet, K., & Rossi-Hansberg, E. (2015). On the spatial economic impact of global warming. *Journal of urban economics*, *88*, 16–37. Elsevier.

Dong, L., Du, R., Kahn, M., Ratti, C., & Zheng, S. (2021). "Ghost cities" versus boom towns: Do China's high-speed rail new towns thrive? *Regional science and urban economics*, *89*, 103682. Elsevier.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from china's national trunk highway system. *The Review of economic studies*, *81*(3), 1046–1070. Oxford University Press (OUP).

Fang C And Liu. (2006). The spatial deprivation and the corresponding controlling paths in China's urbanization process. *Abstracts of the 2006 academic annual meeting of the Geological Society of China (in Chinese)*.

Fujita, M., Krugman, P. R., & Venables, A. (2001). *The Spatial Economy: Cities, Regions, and International Trade*. MIT Press.

Fujita, M., & Mori, T. (1997). Structural stability and evolution of urban systems. *Regional science and urban economics*, *27*(4), 399–442. Elsevier.

Gaotie Web. (2024). *Chinese high-speed railway networks.* Retrieved from Gaotie.cn

Glaeser, E. L., & Kahn, M. E. (2004). Chapter 56 - Sprawl and Urban Growth. In J. V. Henderson & J.-F. Thisse (Éds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2481–2527). Elsevier.

H. Hanson, G. (2005). Market potential, increasing returns and geographic concentration. *Journal of international economics*, *67*(1), 1–24. Elsevier.

Harris Dobkins, L., & Ioannides, Y. M. (2001). Spatial interactions among U.S. cities: 1900–1990. *Regional science and urban economics*, *31*(6), 701–731. Elsevier BV.

Henderson, J. V. (1974). The Sizes and types of cities. *The American economic review*, *64*(4), 640–656. American Economic Association.

Henderson, J. V. (1991). Urban development: theory, fact, and illusion. *OUP Catalogue*. Oxford University Press. Retrieved June 2, 2023, from https://ideas.repec.org/b/oxp/obooks/9780195069020.html

Henderson, J. V., & Ioannides, Y. M. (1981). Aspects of growth in a system of cities. *Journal of urban economics*, *10*(1), 117–139. Elsevier.

Ioannides, Y. (2012). *From Neighborhoods to Nations*. Princeton University Press.

Ioannides, Y. M., & Overman, H. G. (2003). Zipf's law for cities: an empirical examination. *Regional science and urban economics*, *33*(2), 127–137. Elsevier BV.

Ioannides, Y.M., & Wei, S. (2023). The global leapfrogging of urban growth. Retrieved from https://sites.tufts.edu/yioannides/files/2023/08/CRETE_2023_Slides.pdf

Knaap, T. (2006). Trade, location, and wages in the United States. *Regional science and urban economics*, *36*(5), 595–612. Elsevier.

Krugman, P. (1991). History versus expectations. *The quarterly journal of economics*, *106*(2), 651–667. Oxford Academic.

Krugman, P. (1992, November). *A Dynamic Spatial Model*. Working Paper Series. National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w4219

Krugman, P. (1993). On the number and location of cities. *European economic review*, *37*(2-3), 293–298. Elsevier BV.

Lin, Y. (2017). Travel costs and urban specialization patterns: Evidence from China's high speed railway system. *Journal of urban economics*, *98*, 98–123. Elsevier BV.

Lu, J., & Tao, Z. (2009). Trends and determinants of China's industrial agglomeration. *Journal of urban economics*, *65*(2), 167–180. Elsevier.

Lucas, R. E., & Rossi-Hansberg, E. (2002). On the internal structure of cities. *Econometrica: journal of the Econometric Society*, *70*(4), 1445–1476. The Econometric Society.

Mori, T., Smith, T. E., & Hsu, W.-T. (2020). Common power laws for cities and spatial fractal structures. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(12), 6469–6475. National Acad Sciences.

Nagy, D. K., & Others. (2016). City location and economic development. *Princeton University, mimeograph*. crei.cat. Retrieved from http://www.crei.cat/wp-content/uploads/2016/11/jmp_citylocation_nagy-1-1.pdf

Overman, H. G., & Puga, D. (2002). Unemployment clusters across Europe's regions and countries. *Economic policy*, *17*(34), 115–148. Oxford University Press (OUP).

Partridge, M. D., Rickman, D. S., Ali, K., & Olfert, M. R. (2009). Do New Economic Geography agglomeration shadows underlie current population dynamics across the urban hierarchy?*. *Papers in regional science: the journal of the Regional Science Association International*, *88*(2), 445–467. Elsevier.

Poncet, S. (2003). Measuring Chinese domestic and international integration. *China economic review*, *14*(1), 1–21. Elsevier.

Quah, D. T. (1996). Regional convergence clusters across Europe. *European economic review*, *40*(3), 951–958. Elsevier.

Redding, S. J., & Rossi-Hansberg, E. (2017). Quantitative spatial economics. *Annual review of* *economics*, *9*(Volume 9, 2017), 21–58. Annual Reviews.

Redding, S. J., & Sturm, D. M. (2008). The costs of remoteness: evidence from german division and reunification. *The American economic review*, *98*(5), 1766–1797. aeaweb.org.

Redding, S. J., & Turner, M. A. (2015). Chapter 20 - Transportation costs and the spatial organization of economic activity. In G. Duranton, J. V. Henderson, & W. C. Strange (Éds.), *Handbook of regional and urban economics* (Vol. 5, pp. 1339–1398). Elsevier.

Tabuchi, T., & Thisse, J.-F. (2011). A new economic geography model of central places. *Journal of urban economics*, *69*(2), 240–252. Elsevier.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the people's republic of China. *The quarterly journal of economics*, *115*(4), 1091–1135. Oxford University Press (OUP).

Zheng, S., & Kahn, M. E. (2013). China's bullet trains facilitate market integration and mitigate the cost of megacity growth. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(14), E1248–53. National Acad Sciences.