Urban Growth Shadows Revisited: County-Level Evidence from China, 1990–2020[†]

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Abstract

This paper investigates whether a location's growth benefit or suffer from proximity to a big city and explores the underlying mechanisms. Using county-level data from China for 1990–2020, we find that an area's being close to a big city (in the 150–250 km range) reduces its decadal population growth rate by 2.9–3.5 percentage points, which we call the urban growth shadow effect. While previous core–periphery models give transport costs a central role to explain the urban growth shadow effect, we show empirically that for an economy experiencing rapid structural transformation, initial employment share in agriculture is more important than transport costs in explaining the existence of this effect. The mechanism is consistent with high employment share in agriculture constituting a labor pool for migration to urban core areas.

JEL classification: R11, R12, O13, O18

Keywords: Urban growth shadows, Core–periphery patterns, Transport costs, Agriculture, Migration, China

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1 Introduction

How does an area's proximity to a big city affect its growth? This question is of great policy significance as many governments seek to promote regional equity (Kline and Moretti, 2014; Austin et al., 2018; Neumark and Simpson, 2015; Gaubert et al., 2021). If locations near a big city suffer population loss due to geographical proximity to a big city, that fact would imply worsening regional equity in the process of urbanization, especially between the core and peripheral areas within urban agglomerations. Therefore, understanding whether a beneficial effect (also called a spillover effect) or a detrimental effect (also called the growth shadow effect) exists, as well as the conditions under which the effect exists,[1] can inform policy makers' strategies to achieve desirable goals. In theory, the effect of proximity to a big city is ambiguous because, on the one hand, being close to a big city increases competition for resources, which could dampen the growth of the peripheral cities (Krugman, 1993; Fujita et al., 1999). But on the other hand, the presence of nearby clusters of economic activity improves market access, benefiting the growth of smaller neighboring places (Redding and Venables, 2004; Hanson, 2005; Redding and Sturm, 2008; Head and Mayer, 2011; Jack and Novy, 2018).

While previous theories give a central role to transport costs in explaining the core-periphery patterns (Krugman, 1991; Krugman and Venables, 1995; Tabuchi, 1998; Davis, 1998; Fujita et al., 1999; Puga, 1999; Cuberes et al., 2021) , in this paper, we provide evidence that for a country that is still experiencing structural transformation, initial employment share in agriculture is more important than transport costs in explaining the existence of the urban growth shadow effect. We empirically examine this question in the context of China during 1990–2020 because 1990–2020 was a period during which China experienced rapid transformation of its industrial structure and urban landscapes. There was huge variation in the initial agricultural share across counties, and huge improvements in the transportation and commuting infrastructures, which provide an opportunity to assess the relative importance of transport costs and the structural transformation force simultaneously. Moreover, the availability of cross-county migration flow data in China allows us to examine how people moved across space during this period. This is also an advantage not shared by studies that consider early time periods.

In the first part of this paper, we empirically study whether an urban spillover or shadow effect existed in China between 1990 and 2020. We construct a panel dataset of 2,234 Chinese counties[2] with consistent boundaries in this period. We define big cities (which

[1] See Partridge et al. (2009), Beltrán Tapia et al. (2021), and Cuberes et al. (2021).

[2] In our sample, we use administrative units at the county level in China, namely "county level administrative hierarchy," which includes districts (*shixiaqu*), county-level cities (*xianjishi*), and counties (*xian*, *qi*,

are conglomerates of city districts) as the top 20 or 40 largest cities in the beginning of each decade and exclude those cities from our regression sample. We define the primary outcome of interest as decadal population growth of the rest of the counties. We compare the population growth of the counties in concentric rings surrounding their nearest big cities and set counties located 250 km and farther away from the big cities as the baseline comparison group. We find that, compared to the baseline county group, the counties located very close to the nearest big city—within 50 km—grew faster. This positive effect is much stronger and becomes statistically significant during the 2010–2020 period. Meanwhile, counties located at a medium distance—150–250 km—grew significantly more slowly: during every decade between 1990 and 2020, being located within 150–250 km to the nearest big city has a negative effect on decadal population growth, which ranges from 2.9% to 3.5%.

We then investigate what county-level economic variable explains the existence of the urban shadow effect. We focus on two economic variables: access to transportation networks and agricultural employment share. We choose access to transportation networks because transport costs are given a central role in core–periphery models. In particular, Tabuchi (1998) predicts that there is a bell-shaped relationship between transport costs and share of economic activities (population) in core areas. If the economy being examined is on the upward-sloping portion of the curve, then a lower transport cost—captured by better connection to central cities by highways or railways—would predict slower population growth in the periphery areas, resulting in the growth shadow effect. We choose agricultural employment share because it is shown to strongly affect local population growth and the spatial variation in population density (Michaels et al., 2012; Henderson et al., 2018). We find that, when initial access to transportation networks is included in the regression, the coefficient on this term is significantly positive, meaning that being better connected to the core/big city in the beginning predicts *higher* population growth in the subsequent period. This result indicates that the transportation technologies and infrastructure in China had advanced to the stage corresponding to the downward-sloping portion of the bell-shaped curve. Therefore, better transportation access cannot be the reason for the existence of the urban growth shadow effect. In fact, in the regression results, we find that controlling for initial access to transportation networks does not affect the coefficient on the proximity to a big city dummy (150–250km).

Meanwhile, we find that when initial agricultural employment share is included in the regression, the coefficient on the proximity to a big city dummy (150–250km) becomes much smaller and loses statistical significance, indicating that initial agricultural employment share

etc). Each prefectural city core consists of several city districts. In this paper, we use the term "counties" to indicate all units at the county level.

is the "omitted" variable that would lead us to "mistakenly" interpret a negative causal effect of proximity to a big city on growth. We further investigate why initial agricultural employment share plays such a large role in explaining the existence of the urban growth shadow effect. We show that in every period, the employment share in agriculture was larger in locations farther away from the nearest big city, and such an increasing relationship stopped at the distance of about 150km from the nearest big city. Moreover, while initial agricultural share has a negative effect on population growth for an average county, such a relationship is significantly stronger for counties very close to a big city. The combination of both relationships results in the following patterns: for areas very proximate to a big city—where agricultural share has the most negative effect on population growth, agricultural activity there was very limited, so these areas did not grow more slowly, and in fact, they grew significantly faster, probably due to the spillovers from big cities. For areas in medium distances to the nearest big city (150–250km), they had a large agricultural employment share, and at the same time, the effect of initial agricultural share was very negative; as a result, the counties in this distance band grew especially slowly compared to the counties in the rest of the distance bands.

The question is then why initial employment share in agriculture exerts a particularly strong negative effect on a location's growth when this location is close to a big city? We provide evidence that this is because agricultural employees proximate to a big city are particularly easily attracted there to seek job opportunities. For small counties dominated by the agricultural sector, the opportunity costs of migrating out of the local county are much lower; thus, such counties are more likely to lose population in the presence of a nearby big city.[3] We exploit the cross-county migration flow data and estimate a gravity equation to examine this mechanism rigorously. Using bilateral migration flows as the dependent variable, we show that origin county agricultural share predicts a larger number of out-migrants, and agricultural-based counties proximate to a big city are particularly prone to losing population.

In addition to showing that agricultural employment share is crucial to explaining the existence of the urban shadow effect, and the heterogeneity of the growth shadow effect across counties, we also show that agricultural employment share is crucial to explaining the heterogeneous effects of access to transportation networks on growth. In fact, our es-

[3] In theory, migrants can move to any big city instead of the nearest big city, therefore potentially undermining this mechanism. However, in the data we find that migration is highly localized, and short-distance migration dominates. As shown by the China Population Census microdata in 2010, the share of within-province migrants in total migrants was 54.9%, and even for counties located in inland provinces (which are more likely to send out migrants to coastal provinces), the within-province migrant share was 52.9%. Therefore, the presence of a big city can have a large effect on the migration patterns of nearby counties.

timates suggest that the interactive effect between access to transportation networks and initial agricultural employment share is so large that whether a county completely specializes in agriculture determines the sign of the effect of access to transportation networks on population growth.

In the analysis above, the key explanatory variables—initial agricultural employment share and access to transportation networks—are endogenous. While the goal of this paper is not to identify the causal effect of each of these two variables on city growth, we test whether they could explain the urban growth shadow effect. Therefore, we want to rule out the possibility that our findings are driven by some omitted county characteristics. To address this concern, we use agricultural suitability and climatic variables as instruments for initial agricultural employment share, and use access to historical routes as an instrument for the current access to transportation. We show that our core results are robust to the regression estimates using these instruments.

Finally, we discuss the welfare implications of the urban growth shadow effect. Because we find evidence that workers moved across space to arbitrage income differences, the existence of the urban growth shadow effect does not imply a reduction in *aggregate efficiency*. However, we show that proximity to a big city has a large and significant effect on reducing the share of college-educated people and prime-aged (20–44) people in the total population of the periphery counties. Given that college-educated people and prime-aged people contribute more to local fiscal revenues, while the other groups of people presumably consume more public goods in average terms, the urban growth shadow effect implies a form of fiscal transfer from the periphery areas to the core areas. Therefore, government interventions in fiscal transfer might be needed to correct for such fiscal externalities and to promote regional equity.

Our paper contributes to several strands of literature. The first and most related strand of literature has empirically assessed whether big cities imposed negative effects on periphery locations in the context of developed countries, either over a short period (Partridge et al., 2009, in the United States over 1990–2006) or over a long period (Cuberes et al., 2021, in the United States over 1840–2017; Beltrán Tapia et al., 2021, in Spain over 1877–2001). A common finding using long time-span panel data is that at an early stage of economic development, the shadow effect dominates, whereas at a later stage, the spillover effect dominates. Both Cuberes et al. (2021) and Beltrán Tapia et al. (2021) interpret this pattern as resulting from improved transportation and communication technologies over the respective periods, which have allowed for distributing congestion costs among a wider area and have improved market access, thus facilitating the population growth in neighboring locations. In this paper, we show that another economic variable—employment share in agriculture—is more important than transport costs in shaping core–periphery patterns when the agricultural employment share is still high.

The second strand of related literature is a series of studies that link structural transformation to spatial distribution of economic activity (Desmet and Rossi-Hansberg, 2009, 2014; Michaels et al., 2012; Henderson et al., 2018; Eckert and Peters, 2018; Brülhart et al., 2020). In a closely related paper, Brülhart et al. (2020) document employment growth in eight of the world's main economies and find that market potential is losing predictive power for population growth as the economy grows. Their explanation is that at the early stage of development, agricultural employment share is high and structural transformation away from agriculture tends to shift employment to high-density and high-market potential areas. At the later stage of development, however, agricultural share becomes much smaller and the force of falling transport costs plays a more important role. Hence, the peripheral locations suffer increasingly less from remoteness and benefit more from their lower congestion. Because Brülhart et al. (2020) lack a measure of transport costs across space, this important explanation is left untested. Our paper focuses on China during a period of rapid urbanization and structural transformation and uses rich county-level data—especially access to transport networks and county-to-county migration flows—to test the relative importance of transport costs and structural transformation in shaping the core–periphery patterns. Our finding confirms the important role played by agriculture in determining the spatial distribution of economic activity, which is also shown to be important for the U.S. during 1880-2000 (Michaels et al., 2012), as well as for accounting for within-country variation in nightlight intensity on a global scale (Henderson et al., 2018).

Finally, a third branch of related literature is on transportation infrastructure and hinterland development. Existing empirical work shows mixed evidence on the effect of construction of transportation infrastructure on the core–periphery patterns. Baum-Snow et al. (2017) provide evidence that roads and railroads resulted in the decentralization of Chinese cities, the degree of which depends on the configuration of the transportation networks. Banerjee et al. (2020) find that for an average Chinese county, proximity to a highway or railroad is beneficial. However, some argue that improved transportation infrastructure may hurt the growth of the hinterland, leading to reductions in economic growth or losses of population in peripheral counties (Faber, 2014; Qin, 2017; Baum-Snow et al., 2020; Asher and Novosad, 2020). We complement this literature by providing evidence that the effect of transportation infrastructure on the local economy depends crucially on local employment share in agriculture—a finding highly consistent with Asher and Novosad (2020) in the context of India. Thus, our work helps reconcile the mixed evidence found in this literature.

The rest of the paper is organized as follows. Section 2 describes the data and summary statistics. In Section 3, we introduce the empirical model and report the corresponding results. Section 4 discusses the mechanisms behind the effect of a nearby big city. In Section 5, we discuss the welfare implications of the urban growth shadow effect. Finally, Section 6 concludes.

2 Data and Descriptive Statistics

2.1 Data and Measures

In this study, we use counties, prefectural city districts, or prefectural city cores as the basic units of the analysis. In China, each prefectural city consists of two parts: a municipal city core and the peripheral counties. Each municipal city core, in turn, usually consists of several or dozens of city districts. Each county or city core can be viewed as an integrated labor market, and therefore, they are the natural units of the regression analysis. Municipal city cores may have expanded their geographic areas, merged surrounding administrative counties, and formed new city cores. The merged counties are usually reclassified as city districts. For these cases, we treat prefectural city cores within the 1990 administrative boundaries as the units of the regressions, and we treat every surrounding county/city district that was later being merged as a separate regression unit. In addition, the administrative boundaries of counties and city districts have changed over time. To unify these administrative boundaries, we refer to the *Administrative Division Manual of the People's Republic of China* from 1990 to 2020.

We use growth of the resident population as the outcome variable to examine the effect of proximity to a big city on neighboring counties. Data on population of each county come from the *China Population Census* in 1990, 2000, 2010, and 2020. Another main outcome variable is GDP per capita at the county level. We collect the GDP data from the *China Statistical Yearbooks (County-Level)* in 2001, 2011, and 2021. The GDP data of the prefectural city cores come from the *China Urban Statistical Yearbook* of the corresponding years.[4] Because the 1990s was a critical period during which China transitioned from a planned economy to a market economy and a major price reform occurred during this period, the GDP data in the early 1990s are missing. Therefore, our GDP data cover 2000–2020.

We define big cities as the 40 largest prefectural city cores at the beginning of each period (i.e., 1990, 2000, and 2010). As a robustness check, we also define big cities as the 20 largest prefectural city cores. The key explanatory variables in this paper are a set of

[4] For prefectural city cores or counties with missing GDP data, we complement the data with the statistical yearbooks of the corresponding provinces (which provide county-level information).

dummy variables indicating whether a county is close to a large city: $\{I_l^{1-50}, I_l^{50-100}, I_l^{100-150}, I_l^{150-200}, I_l^{200-250}, \ldots\ldots\}$, where I_l^{x-y} equals 1 if the nearest big city to city l is between x and y km; otherwise, it takes the value of 0. We omit the distance category of $\geqslant 250$ km, which means that every distance dummy measures the population growth rate in this area relative to the areas 250 km and farther away from the nearest big city.

In addition to the distance-to-a-big-city dummy variables, we choose two county characteristics, access to transportation networks, and agricultural employment share, to explain the growth of cities. To measure access to transportation networks, we construct two dummy variables indicating whether a county was connected to high-grade highways(*gao dengji gonglu*) and railways at the beginning of each ten-year period, respectively. We use the GIS data of the highways and railways from Baum-Snow et al. (2017) to construct these two variables, which, in turn, are digitized from the road network maps in 1990, 1999, and 2010. Since the information on grades is missing in the 1990 road network maps, we use road density of all roads as an alternative measure for 1990. Data on agricultural employment share come from *China Population Census* in 1990, 2000, and 2010.

To investigate the mechanisms, we need information on the population flows between counties. Such information is rare in a developing country context (Bryan and Morten, 2019). Fortunately, the Chinese census data contain such information. Specifically, the *Chinese Population (Mini) Census Microdata* in 2000, 2010, and 2015 record each individual's *hukou* county (place of hukou registration) and current residence county, which allow us to construct county-to-county migration flows[5].

Finally, as a control variable, we define a dummy variable indicating whether a county is resource-based according to the definition of the *National Sustainable Development Plan for Resource-Based Cities (2013–2020).*

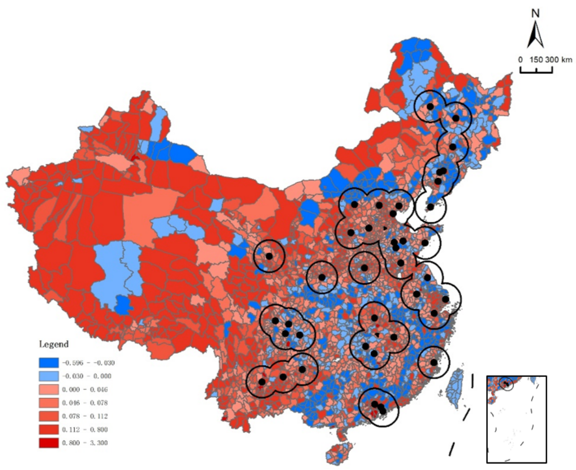
2.2 Summary Statistics

Distribution of the Big Cities. Table A1 in the appendix shows the 40 largest cities and their ranks in each decade. The lists of big cities in 1990 and 2000 are almost the same, and the population rankings of these cities are relatively stable. Figure 1 shows the population growth rate in the three periods in our study. It also plots the distribution of the 40 biggest cities in the beginning of each decade and the 150-km buffer zones around each big city. In the 1990s, we see substantial population growth both in the inland areas and in the coastal areas, as well as in the buffer zones around the big cities. In contrast, in the 2010s, most of the areas in China saw negative population growth, and the growth was

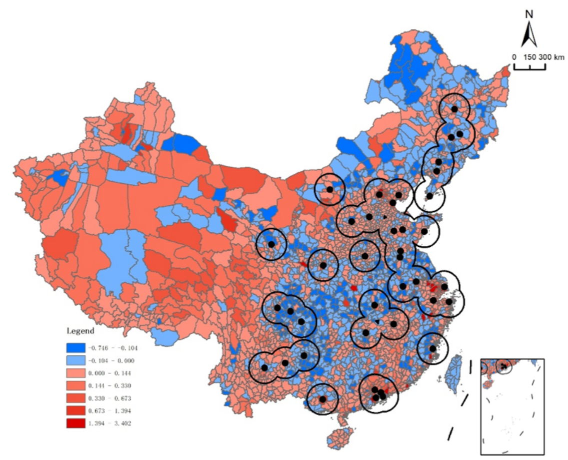
[5] The 1990 census microdata did not record the migration origin information at the county level, and the 2020 census microdata have not been released yet.

mainly concentrated in the areas proximate to a big city and the southeastern coastal areas. Also, compared with the previous two decades, in the 2010s, we see that large cities were significantly more concentrated in the eastern region.

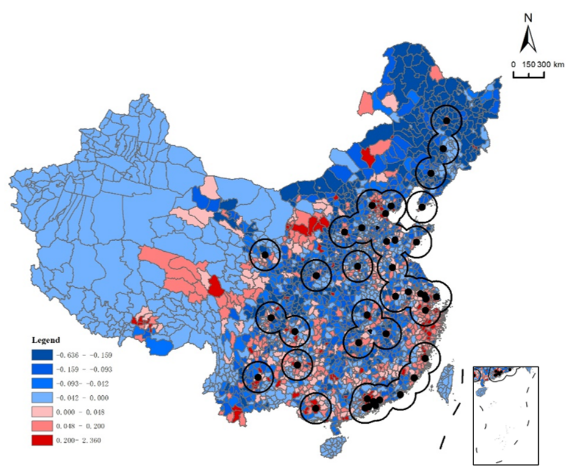
Figure 1: Population Growth Rate from 1990–2020



(a) 1990–2000



(b) 2000–2010



(c) 2010–2020

Notes: Figure 1 plots the population growth rate during the three periods in our study. It also shows the distribution of the 40 biggest cities in the beginning of each decade and the 150 km buffer zones around each big city, which exhibits how the population growth rates of counties near big cities evolved.

Distance to the Big Cities. There are 2,234 county-level observations (excluding big cities) in the sample during 1990–2020.[6] In 1990, the average distance between a county and its nearest large city was 285.61 km, and slightly more than 50% of the counties have a big

[6] For 2010–2020, because some counties have not updated the population data of the latest census, the sample size is slightly smaller compared with the previous two periods.

city neighbor within 165.71 km. The distribution of the distances to the big cities in 2000 and 2010 are similar.

Summary Statistics of the Key Variables. According to the definition of distance ranges above, the sample is divided into seven groups, specifically, big cities, 1–50 km, 50–100 km, 100–150 km, 150–200 km, 200–250 km, and 250+ km (locations that have no large city within 250 km) away from the nearest big city. Table 1 reports the average of the ten-year population growth rate in each distance group, with the distance group of 250+ km used as the comparison group. The population growth rate of big cities is fastest among all seven groups in all three periods, reaching 30% during the 1990s and 2000s, and it slows down to 13.2% during the 2010s. This pattern confirms the visual patterns in Figure 1. In different periods, there are significant differences in the population growth rate across groups. Between 1990 and 2000, the average ten-year population growth rate of the counties located 50–250 km away from a big city is significantly lower (ranging from 2.4% to 5.4%) than the average growth rate of the counties located 250 km and farther away from a big city. Between 2000 and 2010, the average ten-year population growth rate of the counties located within 50 km of a big city is 3.8% significantly higher than that of the counties located 250 km and farther away from a big city. In contrast, the average growth rate of the counties in the 50–250 km distance bands are 3.8% to 5.2% significantly lower than the comparison group. From 2010 to 2020, different from the previous two decades, the average population growth rate in most distance bands is negative, except for the distance group 1–50 km, which shows a significantly higher (14.5%) population growth rate compared to the control group. Meanwhile, the distance group of 150–200km grew by 2.6% more slowly than the comparison group.

Table 1: Population Growth in Different Distance Bins

		Big Cities	1–50km	50–100 km	100–150 km	150–200 km	200–250 km	250 km+
1990–2000	10-year growth rate	0.309	0.088	0.073	0.072	0.043	0.045	0.097
	Difference	0.212***	-0.009	-0.024**	-0.026**	-0.054***	-0.052***	
	Observations	40	131	413	444	336	272	638
2000–2010	10-year growth rate	0.304	0.104	0.028	0.021	0.014	0.018	0.066
	Difference	0.238***	0.038**	-0.038***	-0.045***	-0.052***	-0.047***	
	Observations	40	125	407	453	358	289	602
2010–2020	10-year growth rate	0.132	0.108	-0.025	-0.051	-0.063	-0.056	-0.037
	Difference	0.169***	0.145***	0.012	-0.014	-0.026*	-0.019	
	Observations	40	123	393	440	358	280	520

Notes: Our sample primarily focuses on two geographic units: constant boundary 1990 core cities and the surrounding counties. We divide locations into seven distance bins according to their distance to the nearest big city (regard the big city itself as 0 km) and report average 10-year population growth rate in each bin. We compare the population growth rate of locations in each distance to that of the locations do not have a big city within 250 km and report the difference as well as the significance of the t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In summary, the descriptive statistics show that the big cities grew much faster than the rest of the country, and within an intermediate distance range to a big city, the counties grew significantly more slowly than counties far away from a big city.

3 Econometric Specification and Baseline Results

3.1 Baseline Specification and Results

We use the econometric specification below to estimate the effect of proximity to a big city on the growth of surrounding counties:

$$g_l = \beta I_l + \gamma ln L_l + \delta X_l + \varepsilon_l, \tag{1}$$

where g_l represents the ten-year population growth rate of county l, $I_l \equiv \{I_l^{1-50}, I_l^{50-100}, I_l^{100-150}, I_l^{150-200}, I_l^{200-250}, I_l^{250+}\}$ is a set of dummy variables indicating whether county l's *nearest* big city is within the respective distance range (km). Therefore, only one dummy will take a value of 1, and the rest will take a value of 0. The coefficients 's reflect the effect of being in the corresponding distance band of a big city on growth relative to the control group (distance band 250 km+). We control for the logarithm of the population size of county l at the beginning of the period, $\ln L_l$. We also control for the longitude and latitude of the centroid of each county, a dummy indicating whether the county is resource-based, and three region dummies (eastern region, central region, and northeastern region). All standard errors are clustered at the prefecture level.

Table 2 reports the estimation results of equation 1. The first question we examine is which distance group is most suitable to serve as the control group. To answer this question, in columns (1)–(3), we first add distance-band dummies for every 50 km up to 300 km to a big city, and we use the 300+ km group as the omitted/control group. Compared to the 300+ km distance group, we see that the counties located between 150 and 200 km and those located between 200 and 250 km all show significantly slower population growth rates across the three periods. In contrast, the counties located between 250 km and 300 km of a big city do not show a significantly different population growth rate compared to the 300+ km group in any of the three periods. Therefore, we merge the 250–300 km group with the 300+ km group and use the merged group as the benchmark. Moreover, we find that the growth patterns for the counties located between 150 and 200 km and those located between 200 and 250 km are similar, so as for the counties located between 50 and 100 km and those located between 100 and 150 km. For clarity without loss of information, we merge the

50–100 km county group with the 100–150 km group and merge the 150–200 km group with the 200–250 km group in the benchmark regressions.

Table 2: Population Growth and the Presence of a Big City

	(1) 1990–2000	(2) 2000–2010	(3) 2010–2020		(4) 1990–2000	(5) 2000–2010	(6) 2010–2020
1–50km	0.022	0.034	0.090***	1–50km	0.025	0.038	0.102***
	(0.022)	(0.032)	(0.029)		(0.021)	(0.031)	(0.027)
50–100km	0.004	-0.036**	-0.016	50–150km	0.005	-0.035***	-0.013
	(0.014)	(0.017)	(0.020)		(0.011)	(0.013)	(0.016)
100–150km	-0.001	-0.042**	-0.035*	150–250km	-0.029**	-0.035***	-0.033**
	(0.014)	(0.017)	(0.018)		(0.011)	(0.012)	(0.014)
150–200km	-0.032**	-0.043***	-0.045**				
	(0.014)	(0.016)	(0.018)				
200–250km	-0.031**	-0.036**	-0.047***				
	(0.015)	(0.016)	(0.017)				
250–300km	-0.008	-0.010	-0.032				
	(0.023)	(0.019)	(0.027)				
Observations	2,234	2,234	2,114	Observations	2,234	2,234	2,114
R-squared	0.049	0.071	0.210	R-squared	0.049	0.071	0.207

Notes: Each column presents the result from a regression of average ten-year population growth of locations exclusive of the 40 big cities over the specified period on categorical indicators if the nearest big city is within the specified distance bin. All regressions include a constant and the control variables described in the text. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimation results under this new specification are presented in columns (4)–(6), which are one of the central results of this paper. Similar to columns (1)–(3), across the three periods, the counties located between 150 km and 250 km away from a big city had significantly slower ten-year population growth rates relative to the control group, ranging from 2.9% to 3.5%. The 2000–2010 period (column (5)) shows the strongest urban shadow effect as well as the broadest geographic scope—the counties located between the 50–250 km distance bands, on average, had a significantly lower population growth rate. Coincidently, this is also the decade with the most rapid structural transformation. During the 2010–2020 period (column (6)), we see that the ten-year population growth rate of the counties located within 50 km of a big city is 10.2% faster than the control counties, and such an effect is statistically significant, which suggests that the big cities had a net spillover effect on the surrounding counties. Such a positive spillover effect dies out as we move farther away from the big cities. When we reach the 150–250 km rings, the effect of being proximate to a big city turns significantly negative, suggesting that the urban shadow effect dominates the spillover effect in this distance range. Notice that counties located between 50–150 km did not suffer from the urban growth shadow effect in this period. The reasons for this change will be discussed in Section 4.

We conduct a series of robustness checks of the above core results. First of all, in Figure 1, we see that some provinces, such as Xinjiang and Tibet, contain no big city according to our definition. Most of the counties in these places are more than 250 km away from any of the 40 biggest cities and thus are included in the comparison group. To alleviate the concern that such counties might not be a good benchmark for comparison, we conduct a robustness exercise omitting counties located more than 500 km away from a big city from the analysis. The results are similar and are shown in Table A2 in the appendix.

Secondly, while the above regression analysis defines big cities as the 40 biggest cities in the initial year in China, we also define big cities as the 20 biggest cities in the initial year as a robustness check. We report the results in Table A3 in the appendix, and the results are also similar.

Thirdly, we examine whether the urban growth effect varies across the three largest urban agglomerations: Beijing, Shanghai, and Guangzhou-Shenzhen. We report the results in columns (1), (3), and (5) in Table A4 in the Appendix. Several facts deserve mention. First, across all three agglomerations and all three periods, there is a very large spillover effect in the 1–50 km distance band, ranging from 9.5% (Shanghai, 2010s) to 55% (Beijing, 2000s). Second, there is also large heterogeneity in the growth effect across these three urban agglomerations in the 50–250 km distance range. Consistent with anecdotal evidence, we find Shanghai casted a very strong and far-reaching positive effect on the growth of its peripheral counties, while Beijing casted a much smaller effect on its peripheral counties than Shanghai did. Meanwhile, the Guangzhou-Shenzhen twin-cities imposed a positive effect on surrounding counties in the 1–100 km range in all three periods, but they imposed a large and significantly negative effect on the growth of the counties in the 100–250 km distance range during the 1990s and 2010s.

4 Mechanisms of the Urban Growth Shadow Effect

In Section 3, we established that the urban growth shadow effect exists for an average county located between 150 km and 250 km away from a big city in all three periods and also between 50 km and 150 km away from a big city in the 2000s. However, while some counties have suffered from the presence of a nearby big city, others have not. This leads to the question of whether there is a county characteristic that could explain this heterogeneity, and could absorb the negative effect of the proximity-to-a-big-city dummies (50–150 km, 150–250 km) when being included in the baseline regression. In Subsection 4.1, we test whether access to transportation networks and agricultural employment share can explain the existence and heterogeneity of the urban growth shadow effect. Then, after identifying agricultural employment share as the key county characteristic, in Subsection 4.2, we propose an explanation and provide evidence consistent with this interpretation.

4.1 Local Characteristics and the Urban Shadow Effect

To examine whether access to transportation networks and agricultural employment share can explain the urban shadow effect, we include the corresponding county-level measure as well as the distance-to-a-big-city dummies in one regression and examine whether the inclusion of any characteristic absorbs the negative effect of distance dummies.

We report the results in Table 3. Panel A reports the results for the 1990s. In Panel A, columns (1)–(3), we add initial agricultural employment share, access to highways, and access to railways one by one into the regressions. For ease of comparison, we take the estimates in column (4) in Table 2 here as column (0) in Table 3, which shows that the population growth rate of the counties located between 150 and 250 km away from a big city is 2.9% lower than the comparison counties. However, once we control for initial agricultural employment share of each county, we do not find a significant effect of distance to a big city on population growth. The coefficient on initial agricultural employment share is –0.381, which significantly differs from zero at the 1% level, suggesting that counties with a 10% higher initial agricultural employment share are associated with a 3.81-percentage-point (0.1*0.381) lower ten-year population growth rate. This is probably because agriculture-based economies have lower productivity growth rates, which translates into slower population growth. Notice that from column (0) to column (1), with the addition of one single control variable, the R-squared increases from 0.049 to 0.224, indicating the high explanatory power of initial agricultural employment share in predicting subsequent population growth. Columns (2)–(3) add access to highways and access to railways one by one independently into the regressions. All the coefficients on these two control variables are significantly positive at the 1% level, suggesting that counties with better initial access to highways or railways are associated with faster population growth. However, neither access to highways nor access to railways absorbs the negative effect of the distance dummies.

Panels B and C report the results for the 2000s and the 2010s, respectively. The structure of these two panels is similar to Panel A. We find similar results. First, adding the initial agricultural employment share dummy absorbs the urban shadow effect. Take the results in the 2000s as an example. In column (0), which is taken from column (5) in Table 2, we see a strongly negative effect of proximity to a big city in distance bands between 50–250 km. The negative coefficients for dummies 50–150 km and 150–250 km are both -0.035 and statistically significant. However, once we control for initial agricultural employment, both these two distance dummies become smaller—ranging from –0.013 to –0.015—and statistically insignificant. Second, again, in both panels, adding access to highways and access to railways one by one independently into the regressions does not absorb the urban shadow effect.

Table 3: Mechanisms for the Urban Shadow Effects

Panel A 1990–2000 Period				
	(0) Baseline	(1) Agri share	(2) Highways	(3) Railways
1–50km	0.025	0.028	0.018	0.011
	(0.021)	(0.018)	(0.021)	(0.021)
50–150km	0.005	0.024**	-0.008	0.002
	(0.011)	(0.011)	(0.011)	(0.011)
150–250km	-0.029**	-0.010	-0.036***	-0.027**
	(0.011)	(0.012)	(0.012)	(0.011)
Agri share		-0.381***		
		(0.035)		
Access to highways			0.001***	
			(0.000)	
Access to railways				0.047***
				(0.007)
Observations	2,234	2,234	2,230	2,234
R-squared	0.049	0.224	0.072	0.065

Panel B 2000–2010 Period				
	(0) Baseline	(1) Agri share	(2) Highways	(3) Railways
1–50km	0.038	0.020	0.010	0.028
	(0.031)	(0.025)	(0.032)	(0.031)
50–150km	-0.035***	-0.015	-0.041***	-0.039***
	(0.013)	(0.013)	(0.013)	(0.013)
150–250km	-0.035***	-0.013	-0.035***	-0.039***
	(0.012)	(0.012)	(0.012)	(0.012)
Agri share		-0.391***		
		(0.034)		
Access to highways			0.068***	
			(0.013)	
Access to railways				0.048***
				(0.008)
Observations	2,234	2,234	2,234	2,234
R-squared	0.071	0.260	0.089	0.086

Panel C 2010–2020 Period					
	(0) Baseline	(1) Agri share	(2) Highways	(3) Railways	(4) High-speed
1–50km	0.102***	0.072***	0.095***	0.099***	0.093***
	(0.027)	(0.025)	(0.027)	(0.027)	(0.027)
50–150km	-0.013	-0.008	-0.016	-0.014	-0.015
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
150–250km	-0.033**	-0.022	-0.034**	-0.034**	-0.032**
	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
Agri share		-0.247***			
		(0.028)			
Access to highways			0.030***		
			(0.008)		
Access to railways				0.030***	
				(0.010)	
High-speed dummy					0.057***
					(0.011)
Observations	2,114	2,114	2,114	2,114	2,114
R-squared	0.207	0.272	0.212	0.212	0.225

Notes: We include initial county characteristics in the baseline regression and examine which characteristic absorbs the negative effect of distance. Specifically, we consider initial agricultural employment share, access to highways, and access to railways. Since the information on grades is missing in the 1990 road network maps, we use road density of all roads as an alternative measure for the variable access to highways in year 1990. In 2010–2020, we also consider a high-speed railway dummy. All regressions include a constant and control for initial population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

The strong explanatory power of a location's initial agricultural employment share shown in Table 3 motivates us to explore whether agricultural employment share can also explain the heterogeneity across the three largest urban agglomerations. To do this, we include initial agricultural employment share as an additional control to columns (1), (3), and (5) in Table A4 and report the corresponding results with this control in columns (2), (4), and (6) respectively. In short, while we find substantial heterogeneity in the urban proximity effect across the three urban agglomerations, once we control for each periphery county's own agricultural employment share, a large fraction of this heterogeneity disappears. In particular, we find that while Shanghai had a much stronger urban spillover effect on the peripheral counties compared to the effect imposed by Beijing on its peripheral counties, such a difference can be largely explained by the fact that Beijing is surrounded by more agricultural-based counties.

To summarize, Table 3 shows that across the three periods, the initial agricultural employment share is the county characteristic that well explains the urban shadow effect, while access to transportation networks does not. Tables A4 further shows that the initial agricultural employment share can also explain the heterogeneous effects across the three largest urban agglomerations. There are two possible reasons for why the inclusion of the initial agricultural employment share absorbs the negative effect of proximity to a big city (the largest and most significant being in the 150–250 km distance range). The first reason is that counties located in this distance range are more agricultural-based compared to counties located in the other areas, so they grow more slowly due to their own characteristic, which is independent of the effect of a nearby big city. The second reason is that, in addition to the first mechanism, compared to periphery non-agricultural-based counties, periphery agricultural-based counties are more strongly negatively affected by the presence of a nearby big city. Therefore, the counties located 150–250 km away from a big city grow more slowly due to a combination of their own characteristics and the urban growth shadow effect. In the next subsection, we show in detail that the second interpretation is more consistent with the data.

4.2 The Strong Explanatory Power of Agricultural Employment Share

In this subsection, we explore why initial agricultural employment share has so large power to explain the existence of the urban growth shadow effect, as shown in Table 3. This result is explained by combining following three facts: First, as we show in column (1) in Table 3, a higher value of initial agricultural employment share is associated with a significantly lower population growth rate in all three periods. Second, the spatial distribution of agricultural activity exhibits a pattern—which is reported in Table 4—such that the counties located close to a big city had a lower agricultural employment share, while counties located farther away had a higher agricultural share across 1990, 2000, and 2010. In the years 2000 and 2010, when structural transformation process had reached a later stage, the contrast in agricultural share between the 1–50km distance band and the other distance bands was particularly stark: the gap was 13 and 26.4 percentage-points between the 1–50 km distance band and the 250+km distance band in 2000 and 2010, respectively, whereas this gap was substantially smaller between the distance bands beyond 50 km (which ranges from 1.4 percentage points to 9.6 percentage points in 2000 and 2010). Therefore, the share of agricultural activity decreased at a nonlinear speed (initially fast and then slowly) as one moved away from a big city in 2000 and 2010.

To account for the fact that only counties located at a medium distance to a big city (particularly, 150–250km) suffered a loss in population growth rate, as a third step, we need to further explore whether the agricultural share exerted different influences on the growth of the periphery counties in different distance bands to a big city. To do so, we interact the proximity-to-a-big-city dummies with the initial agricultural employment share and report the results in columns (1)–(3) in Table 5. The coefficient on *agri share* indicates the effect of initial agricultural employment share on population growth for counties located in the 250km+ distance band, and the coefficient on *agri share*x-y km* captures whether initial agricultural employment share has had an additional effect in the corresponding distance band. We find that in general—except for the 2010s between 50 and 250km—the negative effect of agricultural share on population growth becomes more profound as the distance to a big city becomes shorter. Alternatively, this result also suggests that for counties located in the same distance band, say 1–50km, the agricultural-based counties would suffer more from this proximity than would the non-agricultural-based counties.

Table 4: Spatial Distribution of Agricultural Share and Access to Transportation Networks

			Agri share		Access to highways		Access to railways	
	Distance	Obs	Mean	Difference	Mean	Difference	Mean	Difference
1990	1–50 km	129	0.721	-0.033	45.407	18.346***	0.713	0.417***
	50–150 km	856	0.759	0.004	45.308	18.248***	0.485	0.189***
	150–250 km	607	0.780	0.025**	38.889	11.828***	0.381	0.084***
	250+ km	638	0.755		27.061		0.296	
2000	1–50 km	125	0.598	-0.130***	0.600	0.544***	0.704	0.342***
	50–150 km	860	0.705	-0.023**	0.248	0.191***	0.592	0.230***
	150–250 km	647	0.742	0.014	0.111	0.055***	0.527	0.165***
	250+ km	602	0.728		0.056		0.362	
2010	1–50 km	126	0.402	-0.264***	0.913	0.554***	0.754	0.309***
	50–150 km	850	0.570	-0.096***	0.721	0.363***	0.659	0.214***
	150–250 km	644	0.629	-0.037***	0.584	0.226***	0.618	0.173***
	250+ km	614	0.666		0.358		0.445	

Notes: We divide locations into four distance bins according to their distance to the nearest big city and report agricultural share, access to highways (high-grade roads), and access to railways in each bin in corresponding years. Since the information on grades is missing in the road network maps in 1990, we use road density of all roads (m/km^2) as an alternative measure for the variable access to highways in 1990. We compare the mean of these two variables of locations in each distance to that of locations do not have a big city within 250 km. We report the difference as well as the significance of t-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Taking both the spatial distribution of agricultural activity and the interactive effect of agricultural share and proximity to a big city together into consideration, we can explain why only counties located at a medium distance to a big city were negatively affected by the big city in terms of population growth. This is because counties in this area had a relatively high agricultural share, and the negative effect of agricultural share is stronger compared with counties that are 250 km and further away. In contrast, for counties located very close to a big city, although the negative effect of agricultural share is the strongest, agricultural employment activity is very limited there. That is why we do not see any urban shadow effect for these counties; in fact, for this county group, they exhibited much higher population growth rates compared to the counties in the 250+km group (row 1, Panel C of Table 3), suggesting that they may have benefited from the spillovers from the big city.

Table 5: Interactions between the Distance Dummies and the Key Variables

	M = Agri share			M = Access to highways			M = Access to railways		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1990–2000	2000–2010	2010–2020	1990–2000	2000–2010	2010–2020	1990–2000	2000–2010	2010–2020
1–50 km	0.111	0.224**	0.095	0.070**	0.050	0.073	0.021	0.039	0.100**
	(0.094)	(0.093)	(0.058)	(0.035)	(0.036)	(0.072)	(0.033)	(0.047)	(0.045)
50–150 km	0.114*	0.134**	-0.026	0.005	-0.038***	-0.029	0.010	-0.052***	-0.028
	(0.069)	(0.060)	(0.055)	(0.019)	(0.013)	(0.022)	(0.011)	(0.018)	(0.018)
150–250 km	-0.012	0.080	-0.048	-0.040**	-0.035***	-0.056***	-0.020	-0.050***	-0.043**
	(0.067)	(0.056)	(0.059)	(0.020)	(0.012)	(0.020)	(0.012)	(0.017)	(0.018)
M	-0.324***	-0.252***	-0.265***	0.001***	0.102	0.002	0.062***	0.029	0.014
	(0.068)	(0.058)	(0.072)	(0.000)	(0.062)	(0.024)	(0.019)	(0.021)	(0.023)
1–50 km*M	-0.113	-0.309**	-0.067	-0.001**	-0.095	0.040	-0.022	-0.009	0.003
	(0.118)	(0.121)	(0.091)	(0.001)	(0.074)	(0.072)	(0.033)	(0.051)	(0.048)
50–150 km*M	-0.119	-0.206***	0.030	-0.000	-0.035	0.029	-0.020	0.027	0.025
	(0.084)	(0.077)	(0.077)	(0.001)	(0.065)	(0.027)	(0.022)	(0.023)	(0.024)
150–250 km*M	-0.000	-0.128*	0.041	0.000	-0.019	0.045*	-0.019	0.026	0.018
	(0.081)	(0.072)	(0.083)	(0.001)	(0.066)	(0.027)	(0.023)	(0.024)	(0.025)
Observations	2,234	2,234	2,114	2,230	2,234	2,114	2,234	2,234	2,114
R-squared	0.229	0.273	0.273	0.074	0.092	0.214	0.066	0.088	0.213

Notes: We include interaction terms between the distance dummies and agricultural share/access to transportation networks in the baseline regression. Since the information on grades is missing in the road network maps in 1990, we use road density of all roads (m/km^2) as an alternative measure for the variable access to highways in 1990. All regressions include a constant and control for initial population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

As a parallel test, we also examine whether transportation connectivity exhibited some spatial patterns and whether transportation connectivity had differential effects on county population growth in different distance bands to a big city. From the right four columns in Table 4, we see that counties located closer to a big city were more likely to be connected to highways or railways. In columns (4)–(9) in Table 5, we interact the access to transportation networks dummy with proximity-to-a-big-city dummies and report the results. We find that the effect of access to transportation networks on population growth does not vary with the distance to a big city. Therefore, controlling for access to transportation networks does not help explain why the urban growth shadow effect existed only in medium distances to a big city (negative coefficient on the 150–250km distance dummy).

The above findings lead to the following natural question: why does initial agricultural employment share impose a particularly negative effect on a location's growth when this location is close to big cities? An obvious answer is migration: given the much lower value-added per capita of the agricultural sector compared to the non-agricultural sector, the opportunity costs of migrating out of the agriculture-based counties are probably also lower. Therefore, such counties are more likely to lose population in the presence of nearby big cities, especially during a period of structural transformation. We provide evidence to support this conjecture, exploiting the county-to-county migration flow information available in the census microdata.

Specifically, we test whether big cities act as gravitational fields that attract people from nearby areas and whether such gravitational forces are stronger for people coming from agricultural-based counties. To do so, we estimate a gravity equation of migration flows between counties using the census microdata in the years 2000, 2010, and 2015:[7]

$$\begin{aligned} ln\ migration_{od} =& \alpha_0 + \alpha_1\, ln\ pop_o + \alpha_2\, ln\ pop_d + \alpha_3\, ln\ distance_{od} + \alpha_4\, ln\ agrishare_o + \\ & \alpha_5\, ln\ agrishare_d + \alpha_6\, proximity_o + \alpha_7\, proximity_o * ln\ agrishare_o + \varepsilon_{od}, \end{aligned} \tag{2}$$

where $ln\ migration_{od}$ is the logarithm of the number of migrants from origin county o to destination county d. The explanatory variable, $ln\ pop_o$, is the number of residents in origin county o, and $ln\ pop_d$ is the number of residents in destination county d. Variable $ln\ distance_{od}$ is the Euclidean distance between the centroid of origin county o and the centroid of destination county d. In addition to these common explanatory variables in gravity equations, we also include origin county o and destination county d's initial agricultural employment shares in the regressions. While the destination population, pop_d, captures the idea that the magnitude of the gravity force increases with the destination city size, we further add dummies indicating proximity between origin county and a big city destination, $x - y\ km_o$, to capture the idea that the gravity force between origin counties and the big city in close proximity (between x and y km) could be particularly strong. Additionally, we add the interaction term $x - y\ km_o$*$agrishare_o$, the coefficient on which indicates whether big cities particularly attract migrants coming from nearby agricultural-based counties.

[7] We only keep county pairs that have non-zero migration flow in the sample, and therefore the sample size is 74439, 97039, and 40664, respectively.

Table 6: Gravity Equation of Migration Flows

	Log of Origin-Destination Pair Migration Flows					
	2000		2010		2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Population$_o$	0.124***	0.146***	0.145***	0.168***	0.177***	0.201***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Log of Population$_d$	0.073***	0.077***	0.125***	0.130***	0.042***	0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Log of Distance$_{od}$	-0.220***	-0.228***	-0.292***	-0.302***	-0.236***	-0.245***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Log of Agrishare$_o$	0.089***	-0.013	0.147***	0.028***	0.103***	0.036***
	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)	(0.012)
Log of Agrishare$_d$	-0.261***	-0.262***	-0.254***	-0.255***	-0.147***	-0.149***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
1–50 km_o		-0.107***		-0.149***		-0.186***
		(0.017)		(0.017)		(0.031)
50-150 km_o		-0.054***		-0.047***		-0.069***
		(0.010)		(0.010)		(0.015)
150-250 km_o		0.029***		0.048***		-0.008
		(0.011)		(0.010)		(0.016)
Log of Agrishare$_o$ $*$ 1–50 km_o		0.202***		0.182***		0.011
		(0.026)		(0.018)		(0.020)
Log of Agrishare$_o$ $*$ 50–150 km_o		0.163***		0.158***		0.095***
		(0.012)		(0.013)		(0.015)
Log of Agrishare$_o$ $*$ 150–250 km_o		0.158***		0.149***		0.081***
		(0.015)		(0.013)		(0.016)
Observations	74,439	74,439	97,039	97,039	40,664	40,664
R-squared	0.149	0.156	0.181	0.187	0.139	0.144

Notes: Regressions are based on equation 2. Each column reports the results from a regression of origin-destination pair migration flow on population of origin, population of destination and distance between origin and destination. Each observation is a county pair. We keep only county pairs that have non-zero migration flows for each year. In columns (1), (3), and (5), we control for both the initial agricultural employment share of the origin and the destination. Compared with columns (1), (3), and (5), in columns (2), (4), and (6), we further control for categorical indicators for whether the nearest big city of origin county is within the specified distance bin, and for the interaction terms between the origin county's categorical indicators and the origin's initial agricultural employment share. The subscript o and d in the variable names stand for the origin county and the destination county respectively. For example, the variable $1-50\ km_o$ indicates whether the origin county is located within 1–50 km of a big city.

Table 6 reports the estimation results of the gravity equation. We focus on the results for the year 2010 (columns (3) and (4)) because the census data in 2010 records individuals' migration histories during the 2000s—the period in which we find the strongest urban growth shadow effect. Column (3) includes only the most basic explanatory variables, while column (4) includes additional variables to test our proposed mechanism. In both columns, we find that bilateral migration flows are higher when the origin county population size is larger, the destination county population size is larger, or the migration distance is shorter. The significantly positive coefficient on $ln\ agrishare_o$ in column (3) suggests that a higher agricultural employment share in the origin county is associated with a larger number of out-migrants. Crucially, column (4) shows that agricultural employment share of the origin county interacts positively with proximity-to-a-big-city dummies from 1 to 250 km, suggesting that agricultural-based counties with a nearby big city are particularly prone to send out migrants. We also estimate the above gravity equation using the 2000 and 2015 census micro data and find similar results, which show that our proposed mechanism holds across different periods.

4.3 The Power of Agricultural Share in Explaining the Effect of Transportation Access

In subsections 4.1 and 4.2, we showed that agricultural employment share is crucial to explain the existence of the urban shadow effect as well as the heterogeneity of the growth shadow effect across counties. In this subsection, we show that agricultural employment share is also crucial to explain the heterogeneous effects of access to transportation networks on population growth. To do so, we add the interaction term between locations' initial agricultural employment share and access to highways/access to railways into the baseline regressions. We conduct this exercise also because if the rural–urban migration mechanism were at play, we would observe agricultural-based counties that were well-connected to a big city by transportation infrastructure were more likely to lose population.

Table 7 reports the results of this exercise. We find that both the interaction term between the initial agricultural employment share and access to highways and the interaction term between the agricultural share and access to railways are significantly negative during the periods 2000–2010 and 2010–2020, suggesting that places that were both agricultural-based and well-connected to transportation networks grew significantly more slowly. This is likely because better transportation infrastructure facilitates people moving out of their hometowns to seek job opportunities in cities, and such an effect is particularly strong for workers originating from agriculture-dominant counties. This interpretation echoes the finding by Asher and Novosad (2020), who provide evidence that the main effect of new feeder roads is to facilitate the movement of workers out of agriculture in the context of India.

Two additional points are worth noting from the results in Table 7. First, the interactive effect between agricultural share and access to transportation networks is economically very large. Taken column (3) in Table 7 as an example, for a county that had no agriculture at all, being connected to highways predicts a 19.9-percentage-points higher population growth rate over 2000–2010, compared to a county that had no agriculture but was not connected to highways; however, for a county that completely specialized in agriculture (100% agricultural share), being connected to highways predicts a 6.1-percentage-points ((0.260-0.199)*100) lower population growth rate during the same period, compared to a county that completely specialized in agriculture but was not connected to highways. We find that for counties whose agricultural employment share exceeds 76.5%, being connected to highways predicts lower ten-year population growth (0.199/0.26≈0.765). This negative interactive effect is also sizable during 2010–2020. Second, we find that the negative interactive effect between agricultural share and access to transportation networks is strongest during 2000–2010, which is a period with rapid transportation infrastructure improvements,[8] rapid structural transformation, and massive rural to urban migration.

Table 7: The Interactive Effect of Agricultural Share and Transportation Infrastructure on Population Growth

	1990–2000		2000–2010		2010–2020	
	(1) Highways	(2) Railways	(3) Highways	(4) Railways	(5) Highways	(6) Railways
1–50 km	0.028	0.025	0.008	0.018	0.069***	0.075***
	(0.018)	(0.018)	(0.026)	(0.026)	(0.025)	(0.026)
50–150 km	0.019	0.024**	-0.015	-0.014	-0.007	-0.006
	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.015)
150–250 km	-0.014	-0.010	-0.014	-0.013	-0.021	-0.020
	(0.012)	(0.012)	(0.011)	(0.012)	(0.013)	(0.013)
Access to highways/railways	0.000	0.010	0.199***	0.124***	0.079*	0.065**
	(0.001)	(0.053)	(0.050)	(0.045)	(0.044)	(0.027)
Agri share	-0.366***	-0.374***	-0.304***	-0.286***	-0.166***	-0.180***
	(0.057)	(0.054)	(0.033)	(0.047)	(0.059)	(0.036)
Access to highways/railways	-0.000	-0.002	-0.260***	-0.146**	-0.105*	-0.085**
*Agri share	(0.001)	(0.065)	(0.067)	(0.057)	(0.062)	(0.040)
Observations	2,230	2,234	2,234	2,234	2,114	2,114
R-squared	0.228	0.225	0.282	0.268	0.275	0.274

Notes: We include interaction terms between initial agricultural employment share and transportation variables.Since the information on grades is missing in the road network maps in 1990, we use road density of all roads (m/km^2) as an alternative measure for the variable access to highways (high-grade roads) in 1990. All regressions include a constant and control for initial population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

So far, we have established that the agricultural employment share can explain why the urban growth shadow effect exists and the heterogeneity of the shadow effect across

[8] The mileage of expressways increased from 11,600 kilometers in 2000 to 74,100 kilometers in 2010.

counties, while access to transportation networks explains neither. Moreover, we also show that the agricultural employment share explains the heterogeneity of the effect of access to transportation networks. Therefore, we conclude that agricultural employment share plays a more fundamental role in determining economic geography when structural transformation is still ongoing.

4.4 Robustness

In the analysis above, though we measured the key explanatory variables—initial agricultural employment share and access to transportation networks—at the beginning of each period, these two variables are endogenous. Although identifying the causal effect of each of these two variables on city growth is not the main goal of this paper, we aim to find a key county characteristic that could both explain the existence and the heterogeneity of the urban growth shadow effect. Therefore, we want to rule out the possibility that our findings are driven by some omitted county characteristics that are correlated with agricultural share and/or transportation infrastructure and, at the same time, affect local population growth. To address this concern, we construct instrumental variables for initial agricultural employment share and access to transportation networks and test whether our core results are robust to these instruments.

For initial agricultural employment, we use geographical characteristics related to agriculture as instruments. To be specific, we use an index of land suitability—the caloric suitability indices (Galor and Özak, 2016)—together with the average July temperature as instruments for initial agricultural employment share. The caloric suitability indices (CSI) capture the variation in potential crop yield across locations as measured by calories per hectare per year. We first aggregate the pixel-level, time-invariant suitability index for each crop to the Chinese county-crop level. Then, for each county, we average the suitability index across crops to derive a county-level, time-invariable suitability index, and use this index as an instrument for each county's agricultural employment share in each initial year (1990, 2000, and 2010). A large literature in natural sciences and social sciences has shown that temperature is a crucial factor that affects agricultural outputs (Deschênes and Greenstone, 2007; Lobell et al., 2011; Schlenker and Lobell, 2010; Caruso et al., 2016; Blakeslee and Fishman, 2018). Therefore, in addition to CSI, we also use July temperature as an instrument for initial agricultural employment.[9] The idea is these agriculture-related geographical conditions and climate conditions to a large extent determine the size of today's agricultural sector; however, these conditions affect today's population growth only through their impact

[9] Specifically, we determine the average temperature in July using daily temperature data in July between 1960 and 2019 from the Climate Research Unit.

on agricultural development. While this is a strong identification assumption, we believe that with appropriate caveats, the two-stage least squares results are still informative.

We report these IV estimation results and compare them with the OLS results in Panel A of Table A5. Columns (1)–(3) report the results for the 1990s, columns (4)–(6) report the results for the 2000s, and columns (7)–(9) report the results for the 2010s. Columns (1), (4), and (7) report the baseline regression results. Columns (2), (5), and (8) report the OLS results with agricultural employment share as a control variable, and columns (3), (6), and (9) report the IV results. Across all three periods, we find that the IV results are similar to the corresponding OLS results: the coefficients on agricultural employment share have the same sign and similar magnitudes; moreover, in both IV and OLS results, once we control for initial agricultural employment share, the magnitudes of the proximity-to-a-big-city dummies decrease and the statistical significance largely disappears. The robustness of our core results to the instruments lends further credibility to our interpretation, that is, it is the size of the agricultural sector that determines whether the urban growth shadow effect exists.

For the explanatory variables access to highways and access to railways (in the years 1990, 1999, and 2010), we follow Baum-Snow et al. (2017) and use access to railways constructed before 1962 as the instrument.[10] The assumption behind this instrument is that the railroads built before 1962 were constructed according to the dictates of national and provincial annual and five-year plans, which are unlikely to be driven by today's local economic conditions, therefore satisfying the validity assumption. They are relevant instruments because transportation infrastructure is highly durable, so access to transportation networks in the 1960s is highly correlated with the access today.

We report these IV estimation results for access to highways in Panel B of Table A5, and report the IV results for access to railways in Panel C of Table A5. Again, we find that the IV results are similar to the OLS results: the coefficients on the level of transportation infrastructure under OLS are close to those under the IV estimates. Moreover, similar to OLS, under the IV estimates, the inclusion of the transportation infrastructure controls does not absorb the negative effect of proximity to a big city.

5 Welfare Implications of the Urban Shadow Effect

Having established that being close to a big city has a negative effect on population growth at a distance of 150–250 km from the big city during every decade between 1990

[10] Since the information on grades is missing in the road network maps in 1962, we use access to railways in 1962 as an instrument for access to highways (high-grade roads) in year 1999 and 2010. For year 1990, we use road density in 1962 as an instrument for road density in 1990.

and 2020, ranging from 2.9% to 3.5% over ten years, we now explore whether there exists a negative effect of proximity to a big city on the growth rate of GDP per capita, which is another important economic outcome. As mentioned in the data section, due to data limitations, we estimate this set of results for the 2000s and 2010s.

Table 8: Comparison between Population Growth and GDP Growth

	2000–2010		2010–2020	
	(1)	(2)	(3)	(4)
	Population	GDP per capita	Population	GDP per capita
1–50 km	0.038	0.122**	0.102***	0.094*
	(0.031)	(0.061)	(0.027)	(0.056)
50–150 km	-0.035***	0.028	-0.013	0.037
	(0.013)	(0.043)	(0.016)	(0.034)
150–250 km	-0.035***	-0.004	-0.033**	0.013
	(0.012)	(0.037)	(0.014)	(0.033)
Observations	2,234	2,131	2,114	1,994
R-squared	0.071	0.213	0.207	0.480

Notes: This table compares the baseline results of using ten-year population growth rate and of using ten-year GDP per capita growth rate as dependent variables in the specified periods. We regress corresponding dependent variables on categorical indicators if the nearest big city is within the specified distance bin. All regressions include a constant and control for initial population/GDP per capita, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

Table 8 reports the results. Columns (1) and (2) report the results for the 2000s, and columns (3) and (4) report the results for the 2010s. For ease of comparison, column (1) here is taken from the population results in column (5) in Table 2, and column (3) here is taken from the population results in column (6) in Table 2. Columns (2) and (4) report the GDP per capita results in the corresponding periods. We have two findings. First, similar to the results using population growth as the outcome variable, we find that being located within 50 km of a big city has a positive effect on economic growth: the GDP per capita of the counties in this area grew 12.2% faster over 2000–2010 than the GDP per capita growth rate of the control counties, and the GDP per capita of the counties in this area grew 9.4% faster over 2010–2020 than the GDP capita growth rate of the control counties. The effects are statistically significant at the 5% level and 10% level, respectively. Second, in contrast, in the more distant areas from the nearest big city (50–250 km), we find no significant effect of proximity to a big city on the growth rate of GDP per capita. If anything, most of the coefficients in this distance range are slightly positive. The simultaneous population outflow in the peripheral counties and stable relative income growth rates between the core and peripheral areas are consistent with spatial equilibrium: at every point in time, the population moves across the space so that homogeneous individuals derive the same utility/real income in every location. If one place has better economic opportunities than the other places, it will then attract people to migrate there until the real income gap is zero across the space.

Table 9: The Effect of Proximity to a Big City on the Share of High-Skilled Labor and Prime-Aged Population in Periphery Counties

	High School Share			College Share			Prime-Aged Population Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1990–2000	2000–2010	2010–2020	1990–2000	2000–2010	2010–2020	1990–2000	2000–2010	2010–2020
1–50 km	0.630**	3.645***	3.886***	0.065	2.065***	2.456***	-1.585***	0.196	2.534***
	(0.268)	(0.581)	(1.185)	(0.101)	(0.440)	(0.682)	(0.573)	(0.523)	(0.547)
50–150 km	0.342	0.703**	0.126	-0.102*	-0.115	0.157	-1.789***	-1.362***	-0.490
	(0.214)	(0.298)	(0.415)	(0.058)	(0.152)	(0.240)	(0.346)	(0.315)	(0.383)
150–250 km	0.207	0.229	-0.179	-0.037	-0.288**	-0.085	-1.152***	-1.550***	-0.722**
	(0.185)	(0.237)	(0.343)	(0.053)	(0.132)	(0.196)	(0.318)	(0.314)	(0.354)
Observations	2,234	2,234	2,104	2,234	2,234	2,104	2,203	2,213	2,216
R-squared	0.235	0.097	0.074	0.564	0.304	0.259	0.286	0.286	0.324

Notes: This table reports the effect of proximity to a big city on high-skilled labor (defined as high school graduates or college graduates) and prime-aged population (defined as residents aged 20-44). All regressions include a constant and control for initial share of high-skilled labor/prime-aged population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

The changes in GDP per capita could reflect both changes in income levels and/or changes in the composition of the workers. Therefore, we also estimate the effect of proximity to a big city on changes in the share of high-skilled labor (defined as high school graduates or college graduates) and the prime-aged population (20–44) in total population. In columns (1) to (6) in Table 9, we find that, in the areas very proximate to a big city (1–50 km), the share of high-skilled labor increased significantly during 2000–2010 and 2010–2020. As a county's distance to the nearby big city increased, the share of college graduates decreased in the longer distance ranges (column (5) in Table 9). The magnitudes are also sizable: take row 3, column (5) as an example. The estimated coefficient -0.288 implies that the share of college-educated population in total population decreased by 0.288 percentage points over 2000–2010 in the 150–250 km distance band compared to the 250+ km distance band. (The sample mean of the outcome variable was only 2.189 percentage points in 2000.) This pattern provides suggestive evidence that college-educated population are more and more concentrated in the core areas relative to the peripheral areas.[11] Meanwhile, in columns (7)–(9) in Table 9, we find a strong and negative effect of proximity to a big city on the share of the prime-aged population. In the areas between 50 and 250 km to the nearest big city, the share of the prime-aged population decreased significantly across almost all the distance bands and all the periods (except for 50–150 km, 2010–2020), ranging from 0.49 to 1.79 percentage points relative to the control group. This negative effect on the prime-aged labor share has larger magnitudes during 1990–2010, which is consistent with the observation that massive young adults moved from the rural to urban areas in China during this period. This pattern strengthens the urban growth shadow effect: not only in terms of population size, but also in terms of quality of the labor force, big cities act as magnets to attract population from the peripheral areas.

The results of our paper have implications for policy. The existence of the urban growth shadow effect on periphery counties does not necessarily imply welfare losses from the national perspective. The results documented in this paper suggest that a primary reason for why periphery counties of a big city grow more slowly is that individuals migrate from the periphery counties to the big city, and such an action is consistent with income maximization in location choices. Therefore, the existence of the urban growth shadow effect can be perfectly consistent with aggregate efficiency. However, the urban shadow effect also warrants government interventions. The evidence suggests that a disproportionately high fraction of the migrants from the periphery counties to big cities are college-educated and prime-age workers. Those who are left behind in the periphery counties are relatively non-college educated, either very young or very old people. The out-migrants presumably contribute more to the local fiscal revenues compared to their consumption of public goods in per capita terms; those who stay presumably consume more of the local public goods compared to their contributions in per capita terms. Therefore, a strong urban growth shadow effect may become a fiscal burden to the surrounding locations but a fiscal benefit to the big cities. Hence, proper fiscal transfers between the core and periphery locations that correct for such fiscal externalities are required.

[11] From columns (1)–(3) of Table 9, we see some positive effects of proximity to big cities on the changes in the share of high-school graduates in total population for counties located in the 50–250km distance range, though most of such effects are statistically insignificant. This can be explained by the out migration of agricultural workers in these areas, who typically have fewer years of schooling. The out-migration could then raise the share of the population with a high-school degree among the people who stay.

6 Conclusion

In this paper, we use consistent-boundary county-level data from China for 1990–2020 to examine how an area's growth is affected by its geographical proximity to a big city and the mechanisms behind the effects. We find both a spillover effect and a growth shadow effect. On the one hand, compared to the counties located 250 km and farther from a big city, the counties located within 50 km of a big city grew faster, and they grew significantly faster during the 2010s. On the other hand, we find that the counties located at a medium distance grew significantly more slowly: during every decade between 1990 and 2020, a county's being within 150–250 km to a big city reduces decadal population growth by 2.9% to 3.5%. Over time, the spillover effect becomes stronger and the growth shadow effect becomes weaker.

We propose a novel explanation for the existence of the urban growth shadow effect. While previous theories and empirical papers interpret similar overall time trends in other contexts as being driven by improved transportation technologies, we show that whether counties have access to transportation networks cannot explain the existence of the urban shadow effect or the heterogeneity of the urban growth shadow effect across periphery counties. Meanwhile, we find the initial agricultural employment share has much stronger explanatory power. An investigation of the mechanisms suggests the important role played by migration: big cities act as magnets for migrants from nearby regions and also from the entire country. Counties dominated by the agricultural sector are more likely to send out migrants in the presence of nearby big cities because their migrants' opportunity costs are lower. Moreover, agricultural employment share is also a key factor in determining the signs and magnitudes of the effect of access to transportation networks on growth.

Our study derives three policy implications. First, when a country is in the process of structural transformation, big cities on average impose a negative effect on the population growth in the sense that these migrants are presumably more of a fiscal benefit to the receiving cities and those who are left behind are more of a fiscal burden to the periphery counties. Therefore, proper fiscal transfers between the core and periphery locations that correct for such fiscal externalities are required.

Second, in evaluating the local effects of transportation networks that connect periphery counties to the core cities, the share of agricultural employment in periphery counties is a key factor to be considered, which determines the sign and magnitude of such an effect. Better connection to big cities does not always benefit a periphery county—it oftentimes results in a reduction in population growth rate for counties dominated by agriculture. However, better road infrastructure could benefit the local residents by facilitating rural-urban migration and getting access to more job opportunities. Therefore, in per capita terms or in aggregate terms, we might reach different conclusions regarding the local effect of a transportation infrastructure project.

Third, China has a grand national plan to build 19 super regions, and through the massive construction of high-speed rails in the 2010s,[12] the Chinese government aims to decentralize the population from the core cities to the periphery cities in the country. Despite this plan, between 2010 and 2020, the population became increasingly concentrated in big cities. Our results indicate that the massive transportation infrastructure during this period probably did not contribute to more concentration of the population; instead, it probably led to a higher degree of decentralization, as suggested in Baum-Snow et al. (2017). Meanwhile, because China is experiencing a rapid structural transformation process, the movement of agricultural workers from the rural, periphery areas to the non-agricultural sector—which primarily takes place in high-density urban areas—is a major cause for why the population became more concentrated in big cities during this period. As the agricultural sector continues to shrink in the next few decades, and with the further advancement in transportation technologies, the population of China in the future is likely to be more decentralized than the current level.

[12] The mileage of high-speed railways in operation increased from 8,358 kilometers in 2010 to 37,900 kilometers in 2020.

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Appendix

Table A1: List of Big Cities in Each Period

Year	Big Cities
1990	Shanghai, Beijing, Tianjin, Shenyang, Wuhan, Guangzhou, Xi'an, Chongqing, Harbin, Chengdu, Nanjing, Zibo, Dalian, Jinan, Changchun, Qingdao, Taiyuan, Liupanshui, Zhengzhou, Zaozhuang, Dongguan, Shenzhen, Guiyang, Lanzhou, Tangshan, Hangzhou, Anshan, Qiqihar, Tai'an, Fuzhou, Shijiazhuang, Pingxiang, Fushun, Changsha, Nanchang, Yancheng, Neijiang, Kunming, Datong, Suining
2000	Shanghai, Beijing, Shenzhen, Tianjin, Dongguan, Guangzhou, Shenyang, Wuhan, Chengdu, Chongqing, Xi'an, Nanjing, Harbin, Dalian, Jinan, Changchun, Zibo, Qingdao, Zhengzhou, Taiyuan, Kunming, Guiyang, Zhongshan, Hangzhou, Fuzhou, Changsha, Lanzhou, Liupanshui, Zaozhuang, Shijiazhuang, Nanchang, Suining, Nanning, Tangshan, Xuzhou, Jilin, Baotou, Hefei, Ningbo, Anshan
2010	Shanghai, Beijing, Shenzhen, Tianjin, Dongguan, Guangzhou, Chengdu, Wuhan, Xi'an, Shenyang, Nanjing, Chongqing, Harbin, Shantou, Changchun, Zhengzhou, Dalian, Suzhou, Jinan, Qingdao, Wuxi, Nanning, Taiyuan, Hefei, Changzhou, Hangzhou, Zibo, Zhongshan, Changsha, Xuzhou, Xiamen, Guiyang, Fuzhou, Shijiazhuang, Kunming, Lanzhou, Tangshan, Nanchang, Huizhou, Jiangmen

Notes: Our sample primarily focuses on two geographic units: constant boundary 1990 core cities and the surrounding counties. Big cities are defined as the top 40 core cities at the beginning of each decade.

Table A2: Results of Sample Restricting Distance to a Big City

	(1) 1990–2000	(2) 2000–2010	(3) 2010–2020
1–50 km	0.031	0.041	0.109***
	(0.021)	(0.031)	(0.027)
50–150 km	0.011	-0.031**	-0.007
	(0.011)	(0.014)	(0.016)
150–250 km	-0.025**	-0.031**	-0.025*
	(0.012)	(0.012)	(0.015)
Observations	2,023	2,029	1,991
R-squared	0.033	0.058	0.192

Notes: Each column presents the result from a regression of average ten-year population growth of locations exclusive of the 40 big cities over the specified period on categorical indicators if the nearest big city is within the specified distance bin. We leave locations without a big city from 250 km to 500 km as the excluded category as a robustness exercise. All regressions include a constant and the control variables described in the text.

Table A3: Baseline Results for Top 20 Definition

	(1) 1990–2000	(2) 2000–2010	(3) 2010–2020
1–50 km	0.072**	0.125***	0.091**
	(0.035)	(0.044)	(0.039)
50–150 km	0.016	-0.033**	-0.010
	(0.012)	(0.014)	(0.013)
150–250 km	-0.017*	-0.040***	-0.041***
	(0.010)	(0.012)	(0.010)
Observations	2,254	2,254	2,134
R-squared	0.042	0.078	0.200

Notes: Each column presents the result from a regression of average ten-year population growth of locations exclusive of the 20 big cities over the specified period on categorical indicators if the nearest big city is within the specified distance bin. All regressions include a constant and the control variables described in the text. Standard errors are clustered at the prefecture level.

Table A4: Agricultural Share as an Explanation for City Heterogeneity

	1990–2000		2000–2010		2010–2020	
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Agri share	Baseline	Agri share	Baseline	Agri share
Beijing*1–50 km	0.152**	0.090***	0.550**	0.462**	0.282***	0.198***
	(0.064)	(0.029)	(0.238)	(0.198)	(0.074)	(0.048)
Beijing*50–150 km	-0.019	-0.034	0.039	0.043**	0.099*	0.085*
	(0.023)	(0.032)	(0.031)	(0.021)	(0.054)	(0.048)
Beijing*150–250 km	-0.026	0.006	0.010	0.043**	0.003	0.020
	(0.022)	(0.021)	(0.020)	(0.021)	(0.023)	(0.022)
Shanghai*1–50 km	0.118***	-0.066***	0.538***	0.385***	0.095***	-0.006
	(0.013)	(0.023)	(0.013)	(0.019)	(0.014)	(0.017)
Shanghai*50–150 km	0.081**	-0.020	0.248***	0.113*	0.056*	-0.040
	(0.031)	(0.028)	(0.067)	(0.058)	(0.031)	(0.029)
Shanghai*150–250 km	-0.018	-0.073***	0.075**	-0.022	0.042*	-0.038
	(0.028)	(0.023)	(0.031)	(0.027)	(0.026)	(0.027)
Guangshen*1–50 km	0.429***	0.289***	0.222***	0.023	0.227***	0.109
	(0.027)	(0.030)	(0.036)	(0.026)	(0.059)	(0.068)
Guangshen*50–150 km	0.076	0.042	0.200***	0.134**	-0.014	-0.053**
	(0.061)	(0.046)	(0.068)	(0.057)	(0.027)	(0.026)
Guangshen*150–250 km	-0.084**	-0.099***	0.035	0.024	-0.075***	-0.068***
	(0.034)	(0.033)	(0.028)	(0.029)	(0.025)	(0.026)
Agri share		-0.400***		-0.399***		-0.277***
		(0.034)		(0.030)		(0.029)
Observations	2,271	2,271	2,270	2,270	2,150	2,150
R-squared	0.058	0.251	0.118	0.309	0.203	0.282

Notes: We include initial agricultural employment share in the regression of city heterogeneity and examine whether it absorbs the negative effect of distance. All regressions include a constant and control for initial population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.

Table A5: Agriculture and Transportation as Mechanisms for the Urban Growth Shadow

	Panel A Explanatory Power of Initial Agricultural Employment Share								
	1990–2000			2000–2010			2010–2020		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	OLS	IV	Baseline	OLS	IV	Baseline	OLS	IV
1–50 km	0.025	0.028	0.032*	0.038	0.020	0.009	0.102***	0.072***	0.046
	(0.021)	(0.018)	(0.017)	(0.031)	(0.025)	(0.027)	(0.027)	(0.025)	(0.035)
50–150 km	0.005	0.024**	0.019	-0.035***	-0.015	-0.004	-0.013	-0.008	-0.004
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.015)	(0.016)	(0.015)	(0.017)
150–250 km	-0.029**	-0.010	-0.016	-0.035***	-0.013	-0.002	-0.033**	-0.022	-0.013
	(0.011)	(0.012)	(0.014)	(0.012)	(0.012)	(0.015)	(0.014)	(0.013)	(0.018)
Agri share		-0.381***	-0.270*		-0.391***	-0.574***		-0.247***	-0.437**
		(0.035)	(0.156)		(0.034)	(0.149)		(0.028)	(0.214)
Observations	2,234	2,234	2,228	2,234	2,234	2,228	2,114	2,114	2,109
R-squared	0.049	0.224	0.209	0.071	0.260	0.220	0.207	0.272	0.230
	Panel B Explanatory Power of Access to Highways								
	1990–2000			2000–2010			2010–2020		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	OLS	IV	Baseline	OLS	IV	Baseline	OLS	IV
1–50 km	0.025	0.018	0.013	0.038	0.010	-0.051	0.102***	0.095***	0.078***
	(0.021)	(0.021)	(0.021)	(0.031)	(0.032)	(0.037)	(0.027)	(0.027)	(0.030)
50–150 km	0.005	-0.008	-0.013	-0.035***	-0.041***	-0.056***	-0.013	-0.016	-0.024
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
150–250 km	-0.029**	-0.036***	-0.039***	-0.035***	-0.035***	-0.035***	-0.033**	-0.034**	-0.037***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Access to		0.001***	0.002***		0.068***	0.218***		0.030***	0.100**
highways		(0.000)	(0.000)		(0.013)	(0.045)		(0.008)	(0.040)
Observations	2,234	2,230	2,230	2,234	2,234	2,234	2,114	2,114	2,114
R-squared	0.049	0.072	0.068	0.071	0.089		0.207	0.212	0.186

	Panel C Explanatory Power of Access to Railways								
	1990–2000			2000–2010			2010–2020		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	OLS	IV	Baseline	OLS	IV	Baseline	OLS	IV
1–50 km	0.025	0.011	0.005	0.038	0.028	0.020	0.102***	0.099***	0.096***
	(0.021)	(0.021)	(0.020)	(0.031)	(0.031)	(0.031)	(0.027)	(0.027)	(0.027)
50–150 km	0.005	0.002	0.001	-0.035***	-0.039***	-0.042***	-0.013	-0.014	-0.014
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
150–250 km	-0.029**	-0.027**	-0.027**	-0.035***	-0.039***	-0.041***	-0.033**	-0.034**	-0.035**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Access to railways		0.047***	0.067***		0.048***	0.085***		0.030***	0.057**
		(0.007)	(0.012)		(0.008)	(0.016)		(0.010)	(0.022)
Observations	2,234	2,234	2,234	2,234	2,234	2,234	2,114	2,114	2,114
R-squared	0.049	0.065	0.062	0.071	0.086	0.077	0.207	0.212	0.209

Notes: Panel A, Panel B, and Panel C report the results for using initial agricultural employment share, access to highways, and access to railways as mechanisms for the urban shadow effect respectively. In each panel, we compare baseline results, OLS results including corresponding counties' initial characteristics, and 2SLS results for corresponding counties' initial characteristics in the specified period. In Panel A, we use the Caloric Suitability Indices and average temperature in July from 1960–2019 as instruments for initial agricultural employment share. In Panel B, we use road density in 1962 as an instrument for road density in 1990. Since the information on grades is missing in the road network maps in 1962, we use access to railways in 1962 as an instrument for access to highways (high-grade roads) in year 1999 and 2010. In Panel C, we use access to railways in 1962 as an instrument for access to railways in each period. All regressions include a constant and control for initial population, additional geographic control variables, and region dummies as described in the text. Standard errors are clustered at the prefecture level.