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Agglomeration externalities or network externalities? Explaining productivity in Chinese urban regions

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ABSTRACT
This paper explores the relative importance of agglomeration externalities and network externalities in explaining regional productivity through the lens of a polycentric development framework specific to China. Using enterprise investment data, a spatial econometric model and an instrumental variables strategy, we find that both externalities are important in explaining regional productivity. There are no interaction effects between agglomeration and network externalities, with the latter being more prominent in urban regions with higher levels of polycentricity. Compared to agglomeration externalities, which are geographically confined, network externalities can generate spatial spillovers.

KEYWORDS
Agglomeration externalities, network externalities, regional productivity, polycentricity

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1. INTRODUCTION

In an increasingly interconnected world characterised by all kinds of flows and networks, territorial approaches to studying cities and regions need to be complemented with relational approaches (Harrison, 2013). This is now a widely shared idea in the regional science literature and illustrated by the plethora of studies that explore (i) the territorial logic of agglomeration externalities (economic benefits derived from the co-location of economic agents) (Parr, 2002) and (ii) the relational logic of network externalities (economic benefits derived from functional relationships across space) (Capello, 2000).

Comparative analyses of the extent to which both logics matter nonetheless remain inconclusive. The following question, therefore, remains salient:

> (a)re cities, regions, or other types of agglomerations the crucial geographical units of analysis if we want to understand economic development or is it better to focus on the interactions between these units, that is, networks of regions, cities and agglomerations? (Van Meeteren et al., 2016, p. 61)

These fundamental conceptual and methodological questions have major repercussions for the governance of cities and regions in terms of how to best accommodate future urbanisation

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trajectories: is it more beneficial to develop or strengthen urban networks by enabling the exchange of goods, people and information, or should we foster the growth of large and dense cities (Burger & Meijers, 2016)?

This debate is ongoing, not least because of diverging empirical findings. For example, in Western Europe, Meijers et al. (2016) showed that urban network connectivity in corporate networks is more important than urban size for explaining the presence of certain metropolitan functions. In a study of EU27 countries, Camagni et al. (2015) found that second-rank cities sometimes outperform larger metro areas by exploiting the advantages of cooperation with other cities. Similarly, in a Chinese context, Huang et al. (2020) found that the effect of transport network connectivity on per capita GDP growth exceeds that of agglomeration size. However, other studies in a Chinese context, such as that by Yang et al. (2022), came to the opposite conclusion regarding knowledge innovation networks. Despite these different empirical findings, there is a consensus that this is not an 'either-or' question: network and agglomeration externalities can supplement each other, contributing both separately and conjointly (Johansson & Quigley, 2004; McCann & Acs, 2011; Van Meeteren et al., 2016).

This paper disentangles the effects of agglomeration and network externalities and looks at their potential interaction in the Chinese context by focusing on polycentric developments in its urban regions. A polycentric urban region (PUR) can be defined as a region consisting of multiple historically and administratively distinct cities that do not differ much in terms of their importance, are located in close proximity and are well-connected through infrastructure (Kloosterman & Musterd, 2001). In the Chinese context, polycentricity is increasingly promoted as a desirable spatial development strategy to achieve economic development in the broadest sense, and planners have widely adopted it at a range of geographical scales (Cheng & Shaw, 2018; Wang et al., 2019). An expanding body of work has used the PUR concept to understand China's urban and regional development. However, for the most part, these studies have focused on PURs' functional network characteristics (Li & Phelps, 2017), economic potential (Wang et al., 2019) and political and governance context (Li et al., 2023). What is missing is a clear understanding of whether the anticipated benefits of 'agglomeration externalities, economic synergies, and functional specialization' (Li et al., 2023, p. 331) are indeed present in PURs as envisaged and planned.

Against this backdrop, we propose to investigate the agglomeration/network externalities debate in the framework of Chinese urban regions (URs). This is an interesting yet rarely undertaken endeavour since most of the earlier work focused on *city-level* economic effects. The few exceptions include the work of Meijers et al. (2018), who, in a European context, observed that tighter functional, cultural and institutional networks between cities in PURs can enhance the presence of metropolitan functions in the domains of science, economy, culture and sports. Volgmann and Münter (2022), in turn, focusing on German PURs, found that agglomeration externalities – size, density and diversity – influence the growth of metropolitan functions. For the Chinese context, Wang et al. (2022) found that the economic potential of PURs (partly) results from the borrowed size effects that emanate from networking. Although these studies specifically examined (one of the) territorial and relational logics in PURs, they did not explicitly link agglomeration and network externalities in a single analytical framework, nor did they examine how these externalities are organised in URs with different spatial structures. And finally, these studies did not address potential endogeneity issues, mainly because of the absence of data that would allow to test the exogeneity of the alleged relation.

Against this background, this paper addresses the following research questions: *To what extent do network and agglomeration externalities explain regional economic productivity in Chinese URs? And how do these effects differ with the degree of polycentricity?* We address these questions using six formal hypotheses developed in the literature review (Section 2) and subsequently put to the test by drawing on a bespoke methodological framework (Section 3). Section 4 discusses our results, after which Section 5 concludes our paper with an overview of major findings, limitations and avenues for further research.

2. LITERATURE REVIEW

2.1. Agglomeration and network externalities in URs: six hypotheses

Each discussion of agglomeration externalities starts with the truism that geographic proximity is crucial for understanding cities (Parr, 2002; Rosenthal & Strange, 2003). Building on the idea that firms, organisations, households and individuals can benefit from co-locating through sharing, matching and learning, agglomeration externalities have long been deemed the core driving force explaining the growth of cities (Camagni et al., 2017; Puga, 2010). At the same time, it has become increasingly clear that agglomeration externalities are not confined to urban cores but may spill over to nearby centres (Humer et al., 2022; Meijers & Burger, 2010). This is particularly the case in polycentric urban systems, where regionally co-located centres collectively lead to widening geographical scales and scopes of agglomeration externalities (Van Oort et al., 2010). In other words, agglomeration externalities may 'regionalize' (Phelps & Ozawa, 2003), providing more significant economic benefits when the 'assets' of a region are pooled (e.g., agglomerated innovative enterprises in the Guangdong-Hong Kong-Macao Greater Bay area). Given that the positive role of agglomeration on regional economic development in PURs in China has been repeatedly shown in earlier studies (e.g., Li et al., 2019; Li & Liu, 2018), we put forward our first set of hypotheses (*H1* and *H2*):

H1: Agglomeration externalities have a positive impact on regional productivity in URs.
H2: Agglomeration externalities are more prominent in more polycentric URs.

Although studies directly exploring network externalities in PURs are scarce, related discussions can be found in research on 'borrowed size' (Alonso, 1973) and 'agglomeration shadows' (Fujita et al., 2001). Both concepts are akin to network externalities as they describe the positive and negative spillover effects, respectively, of being connected in urban networks. The idea is that, by being located near larger cities in the same PUR, smaller cities can 'borrow' some of the agglomeration economies of these cities and host more functions than their size would typically support (Burger et al., 2015). At the same time, cities may also host fewer functions than their size would normally support because of competition effects (Cardoso & Meijers, 2016). Thus, the overall network benefits delivered to URs as a whole stem from the prevalence of 'borrowed size' over 'agglomeration shadows'. Notably, the effects of both processes depend on the strength of urban networks: borrowed size is more pronounced in the face of strong networks. At the same time, agglomeration shadows are more prominent when strong ties between these cities are absent (Meijers et al., 2016). This suggests that tight urban networks may generate more positive externalities and lead to economic benefits in URs (*H3*). Moreover, Meijers and Burger (2010, 2017) found that in the US and European urban systems, borrowed size is more profound in polycentric areas than areas dominated by a large city, suggesting that network externalities can be enhanced by polycentric development (*H4*):

H3: Network externalities are positively related to regional productivity in URs.
H4: Network externalities are larger in URs with higher levels of polycentricity.

When comparing the extent to which agglomeration/network externalities are likely to operate in URs, a key question concerns the importance of geographical distance. Agglomeration externalities are de facto spatially constrained and, therefore, decline with distance, whereas the effect of distance is considered less prominent or even negligible when it comes to network externalities

(Van Meeteren et al., 2016). Advances in information and communication technologies have made interactions between cities increasingly easy to the degree that, in theory, 'distance does not matter anymore' (Van Meeteren et al., 2016, p. 68). However, in reality, it seems that many types of network externalities taking shape in URs do attenuate with distance. For example, Lim and Han (2021) recently found that geographical distance impacts the formation of innovation networks in East Asian URs and that the effect is more substantial in larger URs. Likewise, Fang et al. (2020) and Zhang et al. (2020) argued that urban networks (economic, transport or virtual connections through social platforms) in China tend to decrease with distance. The fact that the distance between cities in the Yangtze River Delta is, on average, 255 miles compared to 123 miles in the Pearl River Delta is therefore relevant. Thus, it can be expected that:

> H5: The positive influence of network connectivity on regional productivity is stronger in URs where the average inter-city distances are smaller.

A sixth and final hypothesis deals with the potential interaction between both types of externalities. This issue has been raised as far back as the early 1960s (e.g., Nystuen & Dacey, 1961) and highlighted again in recent conceptual papers (Burger & Meijers, 2016; Van Meeteren et al., 2016). Some have argued that agglomeration externalities (indirectly) engender network externalities. The underlying idea is that the geographical concentration of people and economic activities, which are the critical drivers of agglomeration externalities, can lead to reduced transaction or transportation costs between cities (Johansson & Quigley, 2004). This cost reduction makes it more feasible and efficient for individuals, businesses and goods to move beyond cities, thereby strengthening the networking between cities of various kinds (Cainelli & Ganau, 2018). For instance, Burger et al. (2015) pointed out that the close physical proximity and effective accessibility of cities (via road, rail and air) in URs in northwest Europe could support 'borrowed size' effects. Conversely, another perspective suggests that strong network connectivity among cities can substitute for agglomeration externalities typically concentrated at a single point (a single large city) (Burger & Meijers, 2016). This substitution can be achieved through processes such as the sharing of resources and knowledge. Meijers et al. (2018), for example, examined why some PURs seem to be able to exploit their combined urban mass more than others. Based on an empirical analysis of 117 European PURs, they found that the extent to which the constituent cities in PURs are integrated could explain such divergence. As a result, we hypothesise that:

> H6: There is an interaction effect between network and agglomeration externalities affecting regional productivity.

2.2. Overview of previous analytical frameworks

This section briefly reviews the analytical frameworks developed in previous studies to assess network and agglomeration externalities. Key operational aspects include (i) defining 'network connectivity' when measuring network externalities and 'agglomerations' when measuring agglomeration externalities, alongside (ii) how to capture the putative 'economic advantage'. We elaborate on both aspects in turn.

When specifying urban networks, two perspectives are dominant in the literature. First, a 'physical' approach, measuring the strength of infrastructure connectivity (such as aviation, highways and railway networks) (Huang et al., 2020). And second, an 'immaterial' approach, measuring a range of economic, social and cultural aspects, such as political and cooperation networks in WHO programs (Capello, 2000), networks underlying research and patent innovation (Cao et al., 2022), inter-firm relations (Van Oort et al., 2010) and intra-firm relations (Derudder & Taylor, 2016). These enterprise relations, characterising the many processes within and across corporate structures, such as knowledge exchanges and mutual learning and innovation (Martinus & Sigler, 2018), can proxy interactions between cities. Therefore, we construct urban networks within URs through the lens of enterprise investments.

Agglomeration externalities can also be operationalised in myriad ways. While different typologies lead to other proxies (for an overview, see Van Meeteren et al., 2016), here we zoom in on indicators commonly used to capture 'urbanization externalities'. We focus on this externality because it refers to the benefits of the overall concentration of economic activity in a given region, which is expected to be instrumental for the regional economy by providing firms access to extensive markets, access to public infrastructure, etc. (Parr, 2002). Many studies use total urban concentrations to measure agglomeration externalities, such as total urban population (e.g., Meijers et al., 2018; Meijers & Burger, 2010; Ouwehand et al., 2022). Others use density-based measures which reflect population or employment densities (e.g., Li et al., 2022; Li & Liu, 2018). The latter measures would better reflect how economic activities are spatially concentrated (Ciccone & Hall, 1993) and allow to control for differences in the size of geographical areas (Melo et al., 2009).

Different methods have been used for quantifying the hypothesised 'advantages' stemming from network/agglomeration externalities. In the case of network externalities, earlier studies used non-spatial regression-type models (as in Capello, 2000) and count data models (as in Meijers et al., 2016). Alternatively, some scholars turn to spatial econometric tools by specifying spatial weight matrices and modelling spatial spillovers (Yang et al., 2022; Wang et al., 2022). In the case of agglomeration externalities, most recent studies in the polycentricity literature adopt non-spatial models (Ouwehand et al., 2022; Wang et al., 2019). However, as discussed by Van Oort (2007), in the urban growth literature, spatial econometric modelling techniques are also applied to examine the spatial extent of agglomeration externalities.

Importantly, irrespective of the models adopted, a recurring concern is potential endogeneity. In terms of agglomeration externality models, the technique of instrumental variables (IV) analysis (which allows isolating the exogenous effect of urban structure on economic effects) is widely used. When it comes to network externality models, however, constructing IVs is more difficult as it requires historical flow data that are mostly lacking. Consequently, previous studies have avoided this technique but instead verified conditional correlations (e.g., Meijers et al., 2016; Meijers et al., 2018). One exception is Huang et al. (2020), who constructed a spatial weight matrix by multiplying Euclidean distance and train frequency to capture the external relations of cities.

3. METHODOLOGY AND DATA

3.1. Study region

We build our analytical framework around the case of nineteen Chinese 'urban regions' (URs) (see Figure 1). These are administrative regions as outlined in the 14th National Plan, in which economic activities between individual cities are (supposed to be) strongly integrated (Fang, 2015). In 2019, these URs collectively accounted for 70% of all prefecture-level municipalities in China, 29% of land resources, 73% of the total population and around 80% of GDP. A complete list of these URs, alongside socio-economic statistics, is presented in Appendix A in the online supplemental data.

3.2. Measuring polycentricity

For each of these nineteen URs, we calculate a degree of morphological polycentricity by measuring 'balance' in city-size distributions. While there are many ways to measure this (Derudder

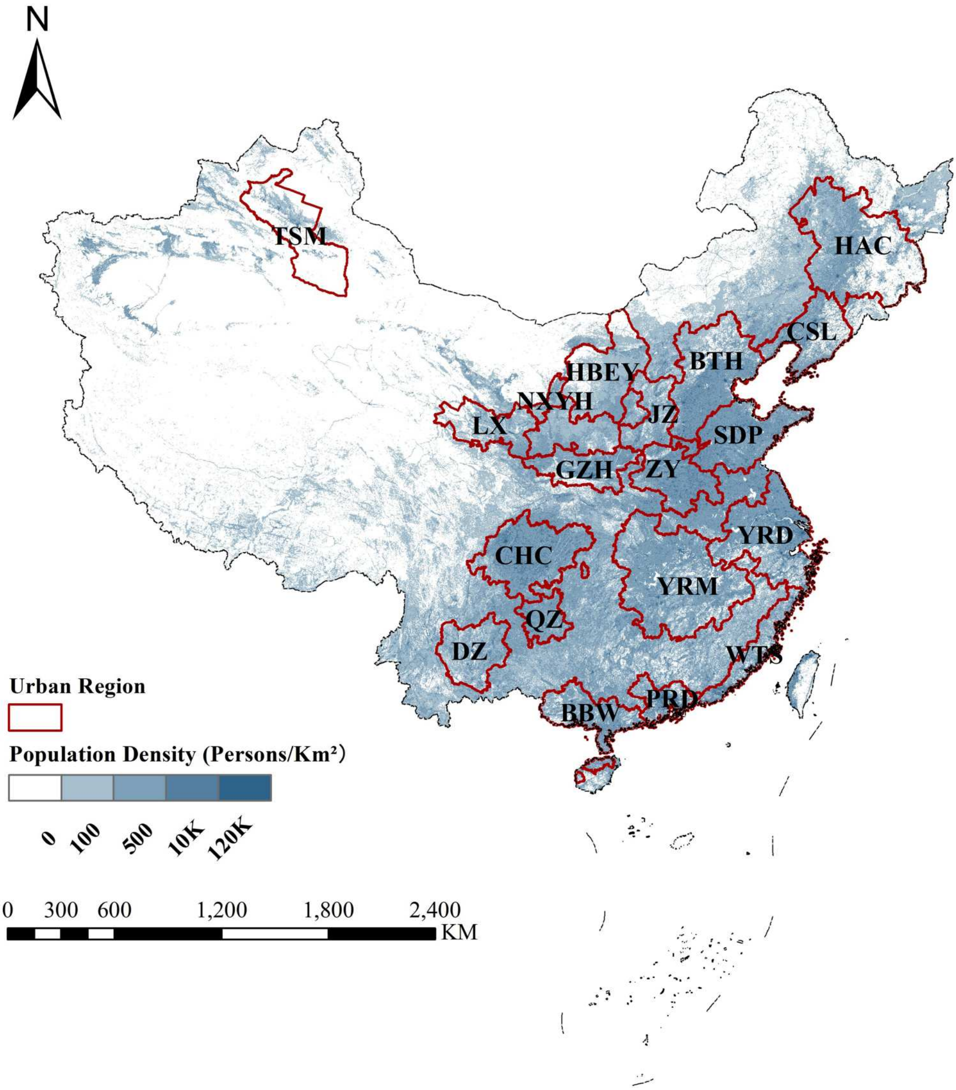

Figure 1. Location of the 19 urban regions under investigation.

et al., 2021), we use a standard deviation-based method (Green, 2007):

$$Poly = 1 - \frac{\sigma_{obs}}{\sigma_{max}} \tag{1}$$

where *Poly* indicates the degree of polycentricity of a UR; σ_{obs} represents the observed standard deviation of the population of all cities in a UR; σ_{max} is the maximum standard deviation in a hypothetical two-city UR where one city has no population and the other has the highest observed population. *Poly* ranges from 0 (no polycentricity) to 1 (an ideal-typical PUR where all cities are equally large). In line with Liu et al. (2019), we identify cities or 'urban centers' based on the LandScan^{TM} population dataset.[1]

3.3. Operationalising agglomerations, network connectivity and regional economic development

An *agglomeration* is measured here by using the population density of an UR, calculated as the number of inhabitants per unit urban area (Li & Liu, 2018).

We construct *urban networks* within URs through the lens of enterprise investments. We first construct a city-to-city matrix by aggregating the enterprise flows between each city pair[2] in the same UR. We then study the network characteristics by using three network-analytical indicators: weighted degree (Equation (2)), weighted clustering coefficient for cities (Equation (3)) and global weighted clustering coefficient for URs (Equation (4)) (Lu & Sun, 2021). The first two indicators reflect the connectivity of a city in the network, while the final one demonstrates the density of the entire urban network at the level of the region:

$$W_i = \sum_{j \in n} E_{ij} n_{ij} \tag{2}$$

Where W_i represents the weighted degree of city i with neighbouring cities in the same UR. E_{ij} is the weight of the edge between city i and j, represented by the level of enterprise investment between i and j ; n_{ij} is the number of cities connected to city i; and n is the total number of cities in the urban network.

$$C_i = \frac{1}{W_i(K_i - 1)} \sum_{(j,k)} \frac{N_{ij} + N_{ik}}{2} a_{ij} a_{ik} a_{ik} \tag{3}$$

Where C_i represents the weighted clustering coefficient for city i. W_i is the weighted degree of city i. K_i is the number of edges between city i and its neighbouring cities. N_{ij} and N_{ik} represent the edge weight between city i with neighbouring cities j and k, respectively. a_{ij}, a_{ik} and a_{jk} capture the presence of connections (i.e., the value equals 1 if the two cities are connected, otherwise the value is 0). We then use Equation (4) to calculate the average value of C_i of all cities in region r to denote the global weighted clustering coefficient G_r of region r:

$$G_r = \frac{1}{n} \sum_{1}^{n} C_i \tag{4}$$

Regional economic development is proxied through labour productivity (LP), operationalised by GDP in the secondary and tertiary sectors divided by the size of the labour force.

3.4. Econometric model

3.4.1. Spatial econometric model

As a first step, we use Moran's I to assess the appropriateness of adopting a spatial econometric approach. We find that the spatial effects are significant[3] and, therefore, introduce a spatial autoregressive model (SAR)[4] to test our hypotheses:

$$LP_{it} = \alpha_1 NET_{it} + \alpha_2 AGG_{it} + \alpha_3 POLY_{it} + \rho M_{ij} LP_{it} + X_{it} + \partial_i + \vartheta_t + \tau_{it} \tag{5}$$

where LP_{it} denotes the labour productivity of UR i in year t; NET_{it} and AGG_{it} represent the density of urban networks (i.e., G_r in Equation (4)) and the population density of UR i in year t, respectively; $POLY_{it}$ is the degree of polycentricity; ∂_i and ϑ_t represent the spatial fixed and time fixed effects, respectively; M_{ij} denotes the spatial weights matrix and ρ is the spatial autoregressive parameter. To verify hypotheses 2, 4, 5 and 6, the interaction items $AGG_{it}*$ $POLY_{it}$, $NET_{it}*$ $POLY_{it}$, $NET_{it}*DIS_i$ and $NET_{it}*$ AGG_{it} are also included. DIS_i denotes the distance between cities within UR i, calculated based on the average driving distance between each city pair[5] within UR i.

The spatial weight matrix M_{ij} is constructed using the inverse geographical distance between different URs. As per Equation (6), the matrix is calculated based on the average driving distance among cities in UR i and j (d_{ij}). In so doing, it is assumed that the matrix through geographical relations does not reflect the economic relations between URs (Huang et al., 2020) so that the spatial spillover effect (if any) can be attributed to the actual inter-city interaction and could thus partly alleviate the endogeneity concern of our model:

$$M_{ij} = \begin{cases} \dfrac{1}{(\sum_{i=1,j=1}^{n,m} d_{ij})_{average}}, & i \neq j, \quad n \in UR\, i, \quad m \in UR\, j \\ 0, \quad i = j \end{cases} \tag{6}$$

Other variables that might determine the level of regional productivity are also controlled for (X_{it}), including the UR's capital stock (i.e., the aggregated amount of physical capital, which is divided by the workforce in the secondary and tertiary sector, 'CLR'), human capital (the ratio of students who received higher education to the total population, 'HUM'), information level (the government expenditure on postal and telecommunications services, 'INF'), industrial level (the ratio of GDP in the secondary industry to that of tertiary industry, 'TIN'), foreign direct investment (the ratio of FDI to GDP, 'FDI'), government intervention (the ratio of government expenditure to revenue, 'GOV').

3.4.2. Dealing with endogeneity

Alongside the potential endogeneity issues with M_{ij}, some of our explanatory variables can also be endogenous. We adopt IVs to deal with this issue. The procedure consists of two steps: (i) we conduct a regression using the endogenous variables as the dependent variable, after which the predicted values from the regression are used as new variables; after which (ii) we regress the independent variables on the newly generated variable. To correctly identify the effects of externalities on regional economic development, the IVs should be correlated with the present-day urban structure but not with present-day economic productivity. For this purpose, and drawing on earlier studies (Ouwehand et al., 2022), we use two historical variables (for AGG and NET) and one predicted variable (for POLY):

(1) population density in 1978 and 1992 (AGG_H);
(2) urban network density in 1978 and 1992 (NET_H);
(3) 'predicted' degree of polycentricity in 2010 and 2019[6] (POLY_P).

AGG_H is constructed in the same way as our present-day variable. As for NET, we build two historical IVs given the rarer interactions between cities in 1978 – the weighted clustering coefficient and counts of inter-city investment within URs. We develop an instrumental variable (POLY_P) for POLY based on geographic obstacles encountered by expanding urban areas. The underlying idea is that urban shapes have a predictive power on polycentricity, as households and firms may account for city shapes by dispersing throughout the urban areas and forming new centres around job locations (Harari, 2020). Furthermore, urban shapes evolve, encountering different sets of geographic constraints (e.g., steep terrain or bodies of water) and subsequently developing in more favourable locations. In other words, POLY_P captures geographical constraints that urban areas face at different stages of their predicted growth. Specifically, we forecast the present urban population (for 2010 and 2019) based on the historical population growth rate (from 1978 to 1992). Details for this IV can be found in Yang et al. (2023).

3.5. Data

The descriptive statistics of all variables and data sources are provided in Appendix B in the online supplemental data. Enterprise data used to construct urban networks were retrieved from Qichacha (www.qichacha.com). Qichacha is one of the largest, most comprehensive websites that provide registration information on all Chinese enterprises (establishing time, location, credit risk, etc.) in China. This platform is renowned for its comprehensive, up-to-date and integrated datasets, and it has been widely used in previous studies in regional science and cognate fields (e.g., Chen et al., 2021; Xu et al., 2023; Zhao et al., 2018). In our research, we extract information regarding the ownership structure of all registered firms (i.e., the distribution of controlling interest in the stock market) to depict the directed connection of inter-city investment flows. Notably, this type of information is commonly used in urban network studies in China, for example, to study spatial–temporal evolution (Yang et al., 2022) or multi-scale characteristics (Guo et al., 2023). As of June 2020, the database we constructed contained 249 million records of firms in the selected 226 cities from 1978 to 2019. We integrate these records into urban networks (as detailed in Section 3.3) for the years 1978 (54 links), 1992 (648 links), 2001 (1511 links), 2010 (2195 links) and 2019 (2709 links). This is not ideal, but the five-year panel data seems sufficient to depict dynamics in regional spatial structure.

4. RESULTS

4.1. Urban networks and polycentricity in Chinese URs

Figure 2 visualises the urban networks and the degrees of polycentricity of URs across China. Three patterns stand out (see Appendix E in the online supplemental data for more detailed figures).

First, the URs with the strongest urban networks are concentrated in coastal China, with Beijing-Tianjin-Hebei (BTH) and the Pearl River Delta (PRD) clearly standing out, alongside other URs like the Yangtze River Delta (YRD) and Shandong Peninsula (SDP). Second, all URs recorded a connectivity rise. Still, this increase is geographically uneven, with especially cities in

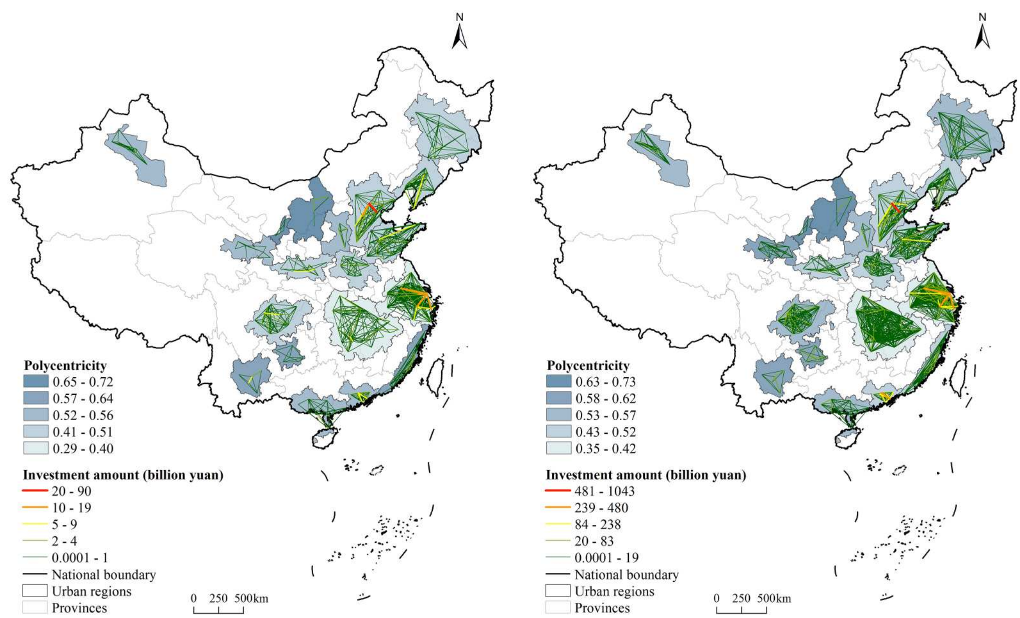

Figure 2. Urban networks and urban polycentricity in URs in China in 2001 and 2019.

the Yangtze River Middle-Reach (YRM) and Chengdu-Chongqing (CHC) becoming more connected (while cities in northeastern and southwestern URs remain poorly connected). Third, URs with stronger inter-urban connectivity are generally also more polycentric, with the strongest polycentricity situated in eastern China (the latter observation has also been documented in Liu et al., 2019).

4.2. Regression results

The stepwise regression results of the SAR model are reported in Table 1. The table is structured into two main sections: *Main effect* and *Spatial autoregressive effect*. *Main effect* reports the local influence of the explanatory variables on a region's productivity; *Spatial autoregressive effect* reflects the influence of dependent variables (productivity) from the neighbouring regions. In general, the *autoregressive* coefficients ρ are significant, showing that spatial spillovers of regional productivity are indeed present. The average R^2 values of all nine models are above 0.65, pointing to a sizeable explanatory power of our models. We now discuss each of these models in turn.

The *first model* is the baseline model and only includes the control variables. The results suggest that productivity is positively associated with the factor inputs (CLR and HUM) and TIN and negatively associated with GOV, in line with the findings of earlier studies (e.g., Yang et al. 2022). These variables are statistically significant and remain broadly consistent across the nine models. The coefficients for INF and FDI have negative signs. For INF, which reflects government investments in communication services, regulation costs may lead to a decline in productivity (Yeo, 2009). The negative influence of FDI may be attributed to its crowding effect on the local economy (Yao & Salim, 2020).

Model 2 includes POLY and indicates that the effect of POLY on LP is significantly positive. Some earlier studies focusing on the Chinese context arrived at opposite conclusions. Still, these differences may be (in part) attributable to the use of different economic measures such as TFP (Yang et al., 2023) and GDP (Wang et al., 2022). Furthermore, our findings align with earlier empirical work that employed a similar economic measure (Wang et al., 2019).

The *third* and *fourth* models include our variables of interest: AGG and AGG*POLY. We find that the increase in population density is an important driver of regional productivity. A 10% increase in population density leads to a 2.6% increase in productivity. However, the regression coefficient for AGG*POLY is not significant, indicating that the benefits from agglomeration are the same across URs with different degrees of polycentricity. This can be explained by businesses and individuals, irrespective of being located in more or less polycentric urban regions, reaping benefits from the proximity and interaction facilitated by high population density. As a result, hypothesis *H1* is accepted while *H2* is rejected.

The *fifth* and *sixth* models include the variable NET and the interaction term NET*POLY. Both variables' coefficients are significant[7], suggesting that (i) network externalities unfold at the UR level and (ii) the impact of NET is more prominent in URs with higher POLY. The latter observation is consistent with Meijers and Burger (2017), who found that borrowed size processes (the positive dimension of network externalities) predominantly occur in polycentric regions. This can also be interpreted as urban networks enhancing the effect of polycentricity on regional productivity. Thus, *H3* and *H4* are accepted.

The *seventh* model includes the interaction term NET*DIS and suggests that there is no evidence that benefits derived from urban networks depend on the geographical distance between cities. *H5* is, therefore, rejected.

Additionally, judging from *Model 8* and its lack of significant sign for the interaction term NET*AGG, we find that agglomeration externalities do not complement network externalities in line with our expectations (*H6)*. This result can be interpreted in two ways: first, a network of cities cannot substitute for the agglomeration externalities of one large city; and second, the advantages of agglomeration may not depend on the interaction between cities.

Table 1. Regression result of SAR.

Variables	Model 1 /	Model 2 POLY	Model 3 AGG	Model 4 AGG*POLY	Model 5 NET	Model 6 NET*POLY	Model 7 NET*DIS	Model 8 NET*AGG	Model 9 ALL
			H1	*H2*	*H3*	*H4*	*H5*	*H6*	
Main									
POLY		0.37 (0.18)**	0.29 (0.12)**	0.35 (0.10)**	0.35 (0.17)**	0.35 (0.16)**	0.48 (0.17)**	0.47 (0.16)**	0.42 (0.22)*
AGG			0.26 (0.10)**	0.27 (0.10)**				0.29 (0.10)**	0.29 (0.09)**
NET					0.09 (0.04)**	0.07 (0.03)**	0.09 (0.04)**	0.08 (0.03)**	0.08 (0.03)**
DIS							−0.37 (0.22)*		−0.37 (0.26)*
CLR	0.23 (0.14)*	0.25 (0.18)*	0.05 (0.01)**	0.04 (0.00)**	0.02 (0.15)*	0.25 (0.18)*	0.20 (0.08)*	0.12 (0.13)**	0.30 (0.17)*
HUM	0.25 (0.11)**	0.16 (0.10)*	0.10 (0.20)	0.06 (0.20)	0.05 (0.01)**	0.17 (0.10)*	0.25 (0.12)*	0.17 (0.20)	0.20 (0.20)
INF	−0.17 (0.09)**	−0.21 (0.09)**	−0.29 (0.08)***	−0.28 (0.08)**	−0.25 (0.08)**	−0.19 (0.08)**	−0.24 (0.08)**	−0.32 (0.08)***	−0.33 (0.08)***
TIN	0.35 (0.26)*	0.53 (0.30)*	0.70 (0.29)**	0.75 (0.29)**	0.45 (0.29)*	0.43 (0.27)*	0.45 (0.10)*	0.62 (0.27)**	0.59 (0.27)
FDI	−0.06 (0.04)*	−0.11 (0.04)**	−0.01 (0.01)*	−0.10 (0.03)**	−0.10 (0.03)**	0.00 (0.03)	−0.10 (0.03)**	−0.10 (0.03)**	−0.13 (0.03)***
GOV	−0.24 (0.10)**	−0.21 (0.10)*	−0.14 (0.10)*	−0.12 (0.10)	−0.14 (0.10)	−0.18 (0.09)**	−0.16 (0.10)*	−0.05 (0.09)	−0.07 (0.09)
NET*DIS							0.17 (0.14)		−0.05 (0.04)
NET*AGG								−0.03 (0.05)	−0.09 (0.04)*
NET*POLY						0.18 (0.07)**			0.32 (0.17)*
AGG*POLY				0.45 (0.47)					0.44 (0.44)
Spatial									
ρ	0.75 (0.05)***	0.75 (0.06)***	0.70 (0.07)***	0.70 (0.07)***	0.65 (0.09)***	0.66 (0.07)***	0.70 (0.11)***	0.65 (0.12)***	0.66 (0.11)***
Observations	57	57	57	57	57	57	57	57	57
R^2	0.67	0.68	0.69	0.69	0.73	0.73	0.73	0.72	0.73

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Std. Err. are in parentheses.

And finally, *Model 9* tests all our hypotheses simultaneously. All the above interpretations still hold, except that the NET*AGG variable becomes statistically significant. The latter may be attributed to the confounding effect from the inclusion of other interaction items, and therefore, we regard results in *Models 1* through *8* as our final findings. We will discuss these results at more length in Section 5.

We now decompose the total impact (impact from the UR itself and proximate URs) of Model 8 (Table 1) into direct impact (impact from the UR itself) and indirect impact (impact from other URs) in Table 2. The results suggest that there is a spatial spillover effect of POLY. While previous studies have identified such an effect concerning environmental effects (Han et al., 2020), our research suggests that spatial spillover effects of POLY may also apply to economic outcomes. Additionally, we observe that AGG is limited to the regional scale, while NET has a larger spatial scope (the indirect effects of NET are significant and positive, while the indirect effects of AGG are not statistically significant). This is in line with Huang et al.'s (2020) observation that network externalities have no obvious geographical boundaries, while spatial spillover effects of agglomeration externalities are not significant.

4.3. Robustness checks

The above results indicate that the degree of urban polycentricity, agglomeration and network externalities are positively related to regional productivity. In this section, we check whether such a finding is robust to (i) the causal direction and (ii) different indices of polycentricity.

4.3.1. Causal relation

The second stage of our IV regressions is reported in Table 3, alongside the standard tests for the relevance and exogeneity of the instruments. Throughout the models, both the tests on the relevance of the excluded instruments and the test of identification provide convincing evidence for the validity of our instrument.[8] From the endogeneity test results, it can be concluded that our variables of interest – POLY, NET and AGG – can be treated as exogenous.[9]

Considering the significance of the IV coefficients in the second-stage results of estimations, we find confirmation of the results reported in Table 1. In particular, along with the positive influence of polycentricity on regional productivity, the effects of agglomeration and network externalities are consistently positive (Models (2) and (3)). In addition, the sizes of the coefficients in these specifications are larger but comparable to those in Table 1.

4.3.2. Alternative polycentricity measurements

Recent studies (Bartosiewicz & Marcińczak, 2020; Derudder et al., 2021; Thomas et al., 2022) highlighted that polycentricity indices can be sensitive to methodological choices. Consequently, findings regarding the economic impact of polycentricity may vary depending on analytical-operational elements. To enhance the robustness of our results, we re-run Model (3) (Table 1) by replacing POLY (standard deviation-based, hereafter referred to as POLY_S) with POLY_P (primacy-based index), POLY_H (Herfindal-based index) and POLY_R (rank size-based index) (details on their calculations are available in Appendix F in the online supplemental data). The findings are presented in Table 5 in Appendix F. We find that Models using POLY_S and POLY_H (Models (1) and (2)) yield consistently positive results. However, the regression coefficients for the other two measures, POLY_P and POLY_R (Models (3) and (4)), are not significant.

It is important to note that these results do not necessarily imply a lack of robustness in our findings. Instead, they provide implications for how differently these measures are formulated and what aspects of polycentricity they capture.[10] We still refer to the result using POLY_S as our conclusion for two reasons. Firstly, POLY_S aligns best to our research focus, specifically in assessing how a population is evenly distributed in space. Secondly, previous studies, such as

Table 2. Results of spatial effect decomposition.

Variables	POLY	AGG	NET	CLR	HUM	INF	TIN	FDI	GOV	NET*AGG
Direct effect	0.22***	0.23**	0.06*	0.04*	0.15*	−0.23**	0.16	−0.05*	−0.11*	−0.03
	(0.02)	(0.10)	(0.03)	(0.01)	(0.10)	(0.08)	(0.24)	(0.03)	(0.06)	(0.06)
Indirect effect	0.33**	0.37	0.08**	0.01	0.26	−0.37*	0.29	0.00	−0.23*	−0.04
	(0.05)	(0.30)	(0.02)	(0.27)	(0.26)	(0.25)	(0.58)	(0.07)	(0.13)	(0.12)
Total effect	0.55**	0.60	0.14*	0.05*	0.41	−0.60**	0.44	−0.05	−0.35*	−0.08
	(0.10)	(0.37)*	(0.10)*	(0.01)	(0.33)	(0.29)	(0.80)	(0.10)	(0.19)	(0.17)

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0$. Std. Err. are in parentheses.

Table 3. Instrumental variable estimation.

Variables	Model (1) POLY_*P*	Model (2) AGG_H	Model (3) NET_H
POLY	0.86 (0.31)**	0.37 (0.16)*	0.67 (0.18)***
AGG		0.35 (0.22)*	
NET			0.06 (0.04)*
CLR	0.05 (0.20)	0.06 (0.14)	0.00 (0.14)
HUM	0.04 (0.10)	0.00 (0.14)	0.03 (0.01)
INF	−0.29 (0.08)***	−0.39 (0.10)***	−0.30 (0.09)***
TIN	0.79 (0.05)***	1.00 (0.30)**	0.68 (0.29)**
FDI	−0.06 (0.05)	−0.02 (0.04)	−0.03 (0.03)
GOV	−0.16 (0.10)*	−0.01 (0.13)	−0.11 (0.12)
Observations	38	38	38
R-squared	0.53	0.53	0.57
Year fixed	YES	YES	YES
F-test of excluded instrument			
POLY	11.03		
AGG		4.46	
NET			6.62
Underidentification test			
Kleibergen-Paap rk LM	5.20**	5.58**	12.30**
Weak identification test			
Cragg-Donald Wald F	23.71	12.46	16.46
LIML size of nominal 5% Wald test (15%)	8.96	8.96	11.59
Overidentification test			
Sargan (score) chi2(1)	/	/	0.56
Endogeneity test			
Durbin-Wu-Hausman chi-sq.	1.46	0.87	0.22
Wu-Hausman	1.28	0.68	0.16

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Std. Err. are in parentheses.

Wang (2021), have established a strong correlation between polycentricity indicators based on standard deviation (in our case, POLY_S) and rank-size regressions (POLY_R). This strong correlation suggests that these two measures can serve as a robustness check for each other in analyses conducted in the Chinese context (Derudder et al., 2021), thus reinforcing the validity of our approach.

5. DISCUSSION AND CONCLUSIONS

Previous studies have examined the importance of a city's embeddedness in various kinds – firms, capital, knowledge, people and goods – to understand its economic performance (Bel & Fageda, 2008; Meijers & Cardoso, 2021; Taylor, 2003). In addition to discussing network benefits at the level of individual cities, this question can also be scrutinised at the level of urban regions: 'What is the aggregate of local outcomes at the network level in terms of regional economic performance?' (Meijers & Burger, 2017, p. 108). And how important are these network advantages *vis-à-vis* agglomeration benefits?

This paper aims to contribute to these debates by situating these questions in the context of polycentric development in China. More specifically, our analysis adds to the existing literature in three main ways. First, we consolidate the concept of network and agglomeration externalities in one framework (Capello, 2000; Parr, 2002). Second, we use spatial-econometric methods to investigate whether network relations provide spatial spillover effects. Third, we adopt an IV strategy, which allows us to collect robust evidence to verify the hypothesised causal effects. The empirical analysis resulted in six main findings:

(1) Both network externalities and agglomeration externalities have a positive impact on regional productivity.
(2) There is no evidence that network externalities attenuate with the distance between cities within urban regions.
(3) Network externalities do not substitute for agglomeration externalities.
(4) Agglomeration externalities remain consistent in urban regions with different degrees of polycentricity.
(5) Network externalities are more prominent in more polycentric urban regions.
(6) Compared to agglomeration externalities, network externalities may spill over on a larger scale.

Finding (1) aligns with previous findings (Li and Liu, 2018; Meijers & Burger, 2010) and hints at the associated advantages of population agglomeration (such as a diversified labour pool, large local markets and strong service provisioning) and network connectivity for regional productivity. Regarding the initial question we posed – is it more beneficial to strengthen urban networks or to foster the growth of large and dense cities? – the answer is nuanced. Providing a definite answer merely through the statistical results can be challenging due to the distinct analytical construction of the two types of externalities (which we will elaborate on later). Nevertheless, our findings highlight the increasing importance of network externalities in Chinese URs for the following three reasons. First, the connectivity between cities in most URs has rapidly increased (Figure 2). Second, compared to agglomeration externalities, network externalities are not restricted to the regional scale (finding 6). Third, more polycentric regions seem more conducive to developing network externalities (finding 5). In contrast, the benefits of agglomeration remain consistent across URs with different degrees of polycentricity (finding 4).

While earlier findings indicated that network externalities depend on cities' local conditions (such as population size), we find that the link between network externalities and regional productivity holds irrespective of specific regional characteristics (in our case, territorial scale represented by the distance between cities) (finding 2). This may be related to using different geographical scales and/or other analytical frameworks. At the scale of the individual city, some have found that network-related benefits differ according to several elements such as urban size (Camagni et al., 2017), development stages (Meijers and Burger, 2017) and position in the network (Huang et al., 2020). The importance of these elements is easy to understand as cities may fulfil different specialised 'roles' in different kinds of urban networks (Meijers & Cardoso, 2021). However, irrespective of which cities benefit (or not) from their functioning in urban networks, network externalities arise at the level of the UR as a whole. If considering URs as spatial units in a larger network, i.e., being part of the national network, the outcomes of being embedded in networks of individual URs may depend on their local conditions (territorial scale). For example, Meijers et al. (2016) found that connectivity in (inter)national networks benefits only a number of URs.

We expect that urban networks would substitute for the benefits of agglomeration to improve regional productivity but do not observe such an effect (finding 3). Two interpretations can be made: first, the benefits of density cannot be replicated by the benefits derived from network development (at least not by the specific type of enterprise network we construct); second, the advantages derived from this type of network are not contingent upon geographical proximity. Similar conclusions have been drawn in several studies: Huang et al. (2020) found that there is no interaction effect between cities' positions in transport networks and benefits of industry agglomeration, and Meijers et al. (2016) found that regional network connectivity (via road, rail and air) cannot substitute for regional size in several metropolitan functions. However, some studies, such as Meijers and Cardoso (2021), support the idea that networks can substitute for size, as they found that cities that are more strongly related to others tend to have more functions than expected. These diverging findings stress the importance of better understanding the *kind* of urban networks that might complement agglomeration effects. After all, as suggested by Burger et al. (2014), urban networks are multiplex phenomena, and one type of functional linkage in a network may substitute for the advantages of agglomeration, while another type might not necessarily do so.

Our final reflection concerns the analytical framework employed in this study. We aimed to examine how agglomeration and network externalities are organised at the UR level. While we operationalised agglomeration externalities on the basis of population density, it was less straightforward to do this for network externalities. Constructing networks at the inter-urban region level (as compared to the city-level) is more challenging due to limited data on interactions between integrated regional units (while city-level data on transportation, knowledge collaboration and financial flows is usually more abundant (Huang et al., 2020)). We devised a twofold approach to capture regional network externalities to address this challenge. Firstly, we introduced a variable representing network density and incorporated it into our regression models. Secondly, we built a spatial weight matrix using the average driving distance between cities in different URs to measure the spillover effect of network connectivity. In other words, we explored the extent to which the connectivity of one urban region influences the productivity of neighbouring URs. In so doing, we treated network externalities as both *local* and *regional* phenomena, assuming that their effects can transcend city boundaries and extend to the broader urban regions. This perspective complements earlier studies that conceptualise network externalities as 'club' goods (i.e., only cities that are partners in the urban networks are influenced) (Camagni & Salone, 1993; Capello, 2000), as well as 'public' goods (i.e., the broader collective of cities (urban regions) are influenced as a whole) (Cornes & Sandler, 1996).

To conclude, our results call for further research in several ways. First, the divergent results stemming from different polycentricity measures suggest that the degree of (morphological) polycentricity may not be as crucial as previously thought. This underscores the importance of integrating network perspectives alongside traditional measures of polycentricity. A shift toward network thinking, which stresses the importance of cities' positions within the inter-city flows of people, information and goods allows for a more comprehensive understanding of urban dynamics. Second, our analysis could be extended by incorporating different sorts of urban networks. The economic benefits of enterprise networks could spill over on a larger scale, which may not be the case with other networks such as air passenger or logistics flows (Zheng et al., 2019). Integrating multi-source data to identify a multiplex urban network may help conduct a more systematic search for network externalities.

Third, we found no geographical distance-decay effect of network externalities. However, sociologically defined types of proximities (e.g., organisation and community proximity) (Boschma, 2005) may play a more critical role than geographical proximity. This needs to be considered when making claims about the proximity-sensitive effect of urban networks. Fourth, our research builds urban networks at the regional scale. Recently, Guo et al. (2023) found that the flow of enterprise investment among cities changed from 'being within-region to primarily being inter-regional' (p. 1). In this respect, it would be interesting to see whether different spatial scales present different network patterns and whether sensitivity issues occur when linking various networks and economic outcomes. Lastly, a consistent application of methods to operationalise agglomeration and network externalities should be adopted in future studies (as in Van Meeteren et al. (2016)). This would provide a precise understanding of the dynamics between different types of externalities, regional spatial structures and regional economic development.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

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NOTES

1 We first create a density file for individual cities and rank individual grids based on their population size. Second, we set a density cut-off at the city's 95-percentile gridded population and select the 5% most populated grids. Third, we combine grids that are eight-adjacent with each other into clusters. Those clusters containing more than 100,000 inhabitants and covering at least 3 km^2 are identified as 'urban centers' and then introduced in Equation (1) at the level of URs.

2 This is a simplification of reality that may not do justice to the complexities of urban and regional processes. In China, small counties are in the sphere of influence of large cities. Hence, cities may not be entirely separate nodes but may be part of a larger agglomeration alongside other not-included nodes. Nevertheless, we adopt this network-analytical approach due to its alignment with our conceptual idea about how cities are interconnected in urban networks.

3 The Moran's I analysis of productivity variable is significant (0.05 with a p-value equalling 0.002 in 2019) for the distance spatial matrix.

4 Four spatial data models have been extensively adopted in the literature, including the spatial autoregressive model (SAR), spatial error model (SEM), spatial lag model (SLM) and spatial Durbin model (SDM). The results of model selection tests are presented in Appendix D in the online supplemental data. Basically, the Lagrange multiplier (LM) tests indicate that the SAR model is more appropriate than the others. Besides, the Hausman test results support the fixed effects model. Therefore, we select the SAR model that includes time and spatial fixed effects in subsequent analysis.

5 The shortest driving times between cities are obtained from the Gaode map product on https://maps.gaode.com/. This map platform provides people with details of fastest travel time and route for different modes of transportation.

6 We use panel data and hence require panel IVs. Since the historical urban networks data are available for 1978 and 1992, we use the two-year data setting (2010 and 2019) in the IV estimation.

7 While we observe a significantly positive influence of NET*POLY, we take additional steps to validate this finding. As suggested by Chu & Zhang (2021), relying solely on the statistical significance for asserting interaction effects could be misleading. There are three potential issues that could compromise the validity of claiming the interaction effect, namely: (1) explanatory

variables are nonlinearly correlated (i.e., the squared terms of the explanatory variable X exhibits strong explanatory power on Y, while X is linearly correlated with Z); (2) tail dependence (i.e., the extreme values in X are associated with extreme values in Z); and (3) heterogeneity (i.e., the variance of errors is constant). Following Chu and Zhang's (2021) suggestions, we conduct several tests (correlation test, tail-dependence test and Breusch-Pagan test) to ascertain the presence of interaction effects in the two variables. The detailed results are provided in Appendix C in the online supplemental data.

[8] The underidentification test examines the null hypothesis that IVs have insufficient power to predict the endogenous variables. The *Kleibergen-Paap rk LM* statistics suggests to reject the hypothesis. The *Cragg-Donald F-statistics* tests whether there is a weak-instrument problem. This is not the case in our models as all the *F-statistics* exceeds the critical values (the bias of IV estimation, relative to the bias of SDM model, did not exceed the threshold of 15%). Finally, as we have more instruments than endogenous variable NET, we conduct an overidentification test to verify if the *additional* instruments are exogenous. The results suggest that there need to be *more* instruments than endogenous regressors.

[9] The endogeneity test is conducted using *Durbin-Wu-Hausman chi-sq* and *Wu-hausman* tests. As both statistics are not significant at a 10% confidence level, we should accept the null hypothesis that there is no endogenous relation between different types of externalities, polycentricity and productivity.

[10] Based on the calculation methods in Appendix E, we summarise the key characteristics of these polycentricity measures. POLY_R evaluates the extent to which the distribution of urban population across different cities adheres to a rank-size distribution. POLY_S, similarly, reflects the extent to which the actual urban population distribution deviates from the maximum standard deviation that could theoretically occur in a two-city urban region. It is important to note that to ensure comparability between different polycentricity indexes, we include all the cities in the calculation of calculate POLY_R, as we did for POLY_S (as suggested by Derudder et al., 2021). Both POLY_R and POLY_S share a common focus on how evenly the population is distributed across all cities, and our calculation reveals a relatively high correlation coefficient between them (0.67). POLY_P, however, is slightly different in that it quantifies the dominance of the largest city within the region. POLY_H measures the degree to which one or a few cities dominate the overall population share. POLY_P and POLY_H exhibit a strong correlation with a coefficient of 0.82. These indicators yield wide-ranging results in terms of polycentricity degree. However, it is worth noting that the operational procedure to measure some of these indicators aligns more closely with the conceptual definition of polycentricity than others. For example, Bartosiewicz and Marcińczak (2020) suggest that POLY_P is more relevant to the process of deconcentration (which is in contrast to the concentration of population in a few dominant cities) than to polycentricity per se. As such, we still refer to the result obtained using POLY_S as our final conclusion.

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