STUDY OF HIGH-SKILL MANUFACTURING IN THE SPACE ECONOMY: UNDERSTANDING THE LOGIC OF NETWORK AND KNOWLEDGE DIFFUSION THROUGH ITS CITIES

by

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ABSTRACT

Daidai Shen. Study of high-skill manufacturing in the space economy: Understanding the logic of network and knowledge diffusion through its cities (Under the direction of DR. Jean-Claude Thill)

The study of city relations and the concept of network analysis have been a major focus in urban and economic geography for decades. Yet, we are still facing many contemporary research challenges on questions regarding the network structures defined by theoretical economic rationale and their implications in the outcomes of knowledge diffusion. In particular, the ever-changing high-tech manufacturing activities continue to challenge the deepening of our understanding of current theories and to advance new theoretical frameworks. Therefore, this dissertation pursues three objectives: the first is to contribute to empirically validate the theoretical conjecture on the notion of city network with consideration of economic rationale. The second is to empirically measure the advantages cities achieve from networking behavior by building a conceptual framework with related schools of thought on innovation and knowledge creation. The third is to advance the new theory of location choice in the era of knowledge-based economy. The main conclusions are three-fold: first, we find the structure of the high-tech city network is consistent with both the complementarity network and the synergy network with a hybrid national core-periphery structure. Second, we find that knowledge diffusion along the organizational network has significant impacts on both innovation and production. However, the effects and strengths are strikingly different for the two high-tech sectors under study. Third, our findings are consistent with the hypothesis that human capital or talent has become the primary determinant of location choice of high-skilled multinational

corporations in a knowledge-intensive economy, thus contributing to the advancement of a new location choice theory.

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CHAPTER 1 : INTRODUCTION

The fundamental idea underlying this dissertation research is that the evolution of high-tech manufacturing activities continues to challenge the deepening of our understanding of current theories and to advance new theoretical frameworks. Confronted with complex and ever-changing realities, the different lines of scientific research developed in the past provide rich perspectives for us to interpret phenomena and develop new theoretical frameworks. This research builds on an extensive body of past research to explain the contemporary high-tech manufacturing activities along three intersecting directions. The first step of research contributes to corroborate the theoretical conjecture regarding city networks based on the economic foundational principles, through empirical validation. The second step delves into quantifying the relative advantages cities achieve from a networking behavior by building a conceptual framework with related schools of thought on innovation and knowledge creation. In the third, we resurface with new insights on knowledge creation by advancing the new theory of location choice in the era of knowledge based economy (as shown in the Fig 1.1).

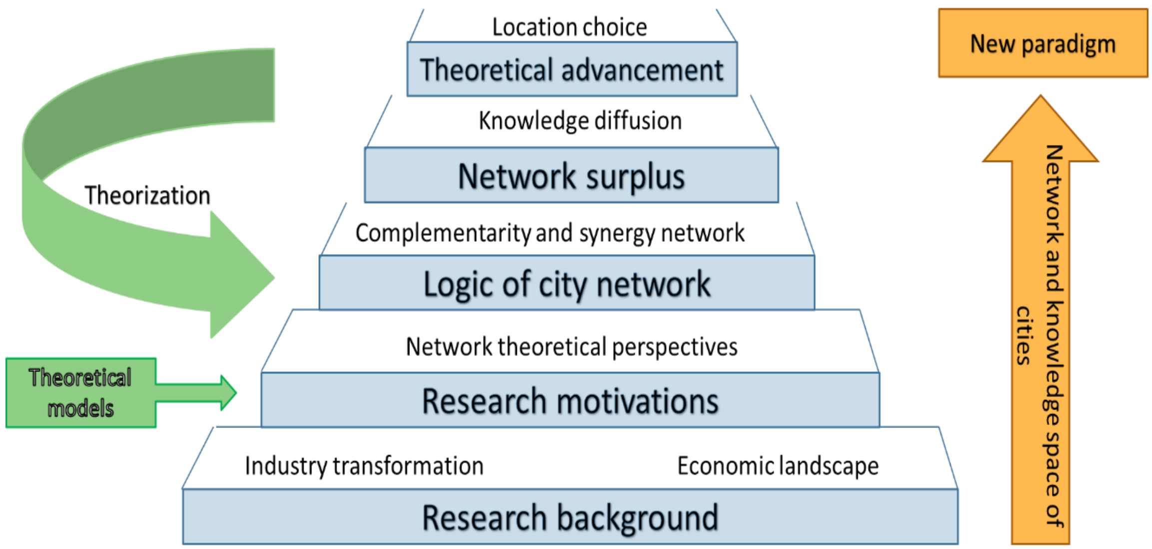


Figure 1.1 Flowchart of research design

Before proceeding to our analysis, it may be useful to make a brief observation on the landscape change of high-tech manufacturing activities over the past decades. In search for effectiveness and economies of scale, high-tech corporations have organized different functions in separate firms, each with a specific competence, all linked in supply chains through the exchange of material and information. Some companies restructured themselves to focus on "core competence" while out-sourcing all of their production activities; on the other hand, other companies continue with a wide range of different businesses under one corporate roof and continue to exhibit vertical structures (Berger 2013). These transformations not only have economic consequences, but also bring about the spatial consequences of those firm behaviors.

Meanwhile, scholars of the economy have evolved their views and often view the economy as a system of interactions among individuals, firms and institutions. In this vein, the concepts of network and networking have become commonplace for the analysis of many phenomena in economic and urban geography including systems of cities, innovation and organizational networks, and global production networks (Camagni and Capello 2004; Glückler and Doreian

2016; Peris, Meijers, and van Ham 2018; Thill 2018). Relevant theoretical contributions have been constructed in order to interpret such spatial phenomena and estimate socioeconomic consequences at the various spatial scale, such as a large region, a nation or the global scale.

Several theoretical positions exist that encompass various approaches to reflect the different aspects of intercity relations. With the complex notions and expressions involved in the studies of a set of interdependent cities, some research gains insights into the multiplexity of urban networks at regional level, such as the notion of polycentric urban regions, and apply a network approach based on the commuting flows relying on geographical information systems (Burger, van der Knaap, and Wall 2014; Curtin 2007; Hall and Pain 2006; Wen and Thill 2016). There is also a group of study that focuses on the urban system from the global perspective which first and foremost studies world cities and world city network building on mathematics model (Taylor 2010; Taylor and Derudder 2017). Along with the computational trend in social science, the methodological progresses in this field draw their inspirations from computer and network science, that have created new tools to study the network processes from various angles (Batty 2007; Bretagnolle and Pumain 2010; Zhang and Thill 2019).

These theoretical and methodological building blocks provide us the essentials for refinements and the new creation of concepts and theories. Early contributions to the systems of cities claim that the classical central place model may not be well explaining contemporary structure of city system in the context of intercity relations. The conceptualization of city network has been claimed as a successful theoretical framework of a new organizational structure of the modern urban system, which overcomes the explainable limitation of the traditional central place model (Camagni, Capello, & Caragliu, 2013). In this case, the conceptual framework of city network with complex theoretical foundations and hypotheses seeks to consider cities as agents and to interpret the organization of city-system based on two types of network behavior, namely a complementarity network and a synergy network. A complementarity urban network entails that the cities not only be specialized in different economic activities, but also participate in spatial economic interactions and hence integration; meanwhile, synergy networks are comprised of similar centers for innovation cooperation to overcome internal know-how weaknesses (Meijers 2005; van Oort, Burger, and Raspe 2010).

In spite of the upsurge of literature on networks and urban systems, little attention has been paid to validate the underlying theory of city network with the consideration of economic rationale that reflects the manufacturing activities. As a result, the first part of the research is to contribute to corroborate the theoretical conjecture regarding the city network through empirical validation. According to the logic of complementarities and synergy network, we assume that the two types of network co-exist in the system of cities as innovation is a crucial function in high-tech manufacturing. Therefore, with a dataset of high-tech private manufacturing firms in Chinese prefectural cities, this research is dedicated to examining the organizational logic of advanced manufacturing cities using a mesoscale inferential approach (Aicher, Jacobs, and Clauset 2015) from network science to identify the connectivity pattern of cities based on their functional interaction. Two research questions, particularly, are concerned: first, does the city network as a new spatial paradigm really exist, given its specific meaning and the economic rationale that underpins it? Second, what organizational logic regulates how cities interact with each other to produce the observed network behavior of high-tech firms?

The following chapter is devoted to assessing the impacts of city network on knowledge diffusion and innovation. Although it is essential to provide empirical evidence for the abstract theory of city network, the measurement of network externalities and their implications for the cooperative outcomes will in turn help to theorize the relational thinking in the field. In line with knowledge-based theory and endogenous growth model, various schools of economic thought have developed to tackle questions of innovation and knowledge diffusion. Theories on geographic clustering of businesses are dominant in understanding the process of knowledge spillover and how geographic proximity may facilitate it (Henderson 2003; Rosenthal & Strange 2004). Later, the network concept and evolution in economic geography have brought deeper insights into the field of knowledge spillover and innovation. Especially, recently proposed concept of technological relatedness with the ability of breaking geographical limitation is anticipated to have positive impacts on the scope of knowledge spillovers both in short and long terms.

Since the 1950s, the literature on knowledge diffusion and creation has been largely developed and expanded, but the fragmentation of current research still appears. Although progress has been made on theories closely articulating innovation and organizational relations, the extant research is still too scarce to have established consensus theories of knowledge spillover and innovation (Glückler 2014; Ter Wal 2014). For example, there is little we know about the mechanism of knowledge spillover in terms of various technological relatedness embedded in the micro organizational relations, such as headquarters and subsidiaries in high-tech manufacturing. In particular, organizational networks contain a wide range of business relationships with both geographic proximity and social networking, such as headquarters and subsidiaries.

In this chapter, we develops a conceptual framework that takes into account industrial clustering, organizational networking and technological relatedness to assess their impacts on knowledge diffusion by placing the city at the heart of this process. Empirical evidence based on a new data set on Chinese cities and high-tech industries is used to test the effectiveness of theories on different types of knowledge and industrial modes –from fast- (biotech) to slow-changing (technology hardware and equipment) knowledge-based sectors. Our research is not only dedicated to tackling the research challenges we are facing regarding the implications of organizational network in knowledge diffusion but also pushing the boundaries of various theoretical thoughts in refining the concept of technological relatedness and enhance the relational thinking in conceptualizing the space economy with our quantitative empirical evidence. We mainly focus on three research questions: first, does the organizational city network contribute to knowledge spillovers across territories? Second, what types of knowledge spillovers occur between cities, and what is their impact on cities' absorptive and learning capacity in the city network context? Third, are there any differences across various industrial activities?

We thus arrive to chapter 4, which is a contribution to the advancement of new location choice theory. Multinational corporations are one of the key actors in the study of intercity relations at the global scale. Recent theoretical concerns argue that traditional theories are unable to explain the location decisions of contemporary firms, particularly those large corporations with increased mobility. Agglomeration theory has been dominant in the traditional locational theory for decades since the Fordist industrial era. Industrial agglomeration or clusters has been considered as the key element to location decisions of corporations (Krugman 1990; Porter 2000). However, with the evolution from the industrial era to post-industrial and knowledge economies, a radical shift in research has started to focus on the influence of innovation ecosystems and the role of human capital in determining the locational decision of firms in post-industrial capitalism.

As the largest foreign investment recipient country, China has been characterized by an uneven distribution of foreign investment across the country. In 2008, 1,546 high-tech subsidiaries of global multinationals were located in only 54 large cities. Under the classical paradigm for location choice, early studies on the locational decision of multinational firms mainly focus on traditional perspectives such as industrial clusters, tax rate, or market size to address the leading strategy of minimizing costs. Yet, there has been an increasing change in the geography of corporations that the locations of modern knowledge-based firms are less restricted by cost considerations, but more often driven by access to high-skill worker or talent in knowledge-based economy.

Therefore, drawing on the literature on the location choice of multinational units and their geographical implications, this chapter tries to advance the theory of location choice in knowledge-based economies with a focus on human capital. Our core hypothesis is that the location choices of high-skill multinational manufacturing units will favor places with large concentrations of human capital as talent or human capital has become a key factor of location and relocation of large corporations and headquarters. We further test whether the interplay of economic institution and cultural distance helps to shape the location choices of high-tech MNC firms when considering the role of human capital. In this chapter, therefore, we study the location of 1,526 high-tech MNC units in five economic regions in year 2008 to test these hypotheses. We estimate mixed discrete choice models to examine the relative importance of human capital, economic institution and cultural distance variables alongside measures that have been proposed in other studies of the determinants of location decision of multinational firms.

The rest of the dissertation is structured as follows: Chapter two discusses the city network paradigm set on economic foundations; Chapter three presents evidence of city in innovation from the perspective of networking; Chapter four attempts to advance the new theory of location in knowledge based economy. Finally, conclusions of this dissertation research are presented in Chapter five.

CHAPTER 2 : ON THE ECONOMIC FOUNDATION OF THE CITY NETWORK PARADIGM: EVIDENCE FROM HIGH-TECH FIRMS IN CHINA

In the light of the city network paradigm of urban economic structure, this section empirically examines the underpinnings of advanced manufacturing cities in China. Weighted stochastic block modeling of meso-scale structures supplement degree centralities are used to test how industrial network linkages of complementarity and synergy configure city networks. Using data on headquarters-subsidiary relationships, we find the structure of the high-tech city network is consistent with both the complementarity network and the synergy network. Second, a hybrid national core-periphery structure with regional community best describes the meso-scale properties. Third, there are variations according to high-tech sectors.

2.1. Introduction

Cities are commonly regarded as the linchpin of the socio-economic organization of contemporary societies within the frame of national territories. As such, the thick web of functional interdependencies among cities make it compelling to view a country as a system. As the primary theoretical framework on this matter, central place theory has been repeatedly tested and adapted to explain the structure of national city systems (Neal 2011; Pacione 2013). However, given its intrinsic theoretical limitations, central place theory has largely lost its interpretative power in contemporary societies. Meanwhile, the paradigm of city network has gained prominence in scientific contexts to define the new theoretical underpinnings of the urban economic structure since the late 20th century (Camagni and Capello 2004; Dicken et al. 2001; Glückler 2007; Glückler and Doreian 2016; Huggins and Thompson 2013; M. Castells 1996; Peris, Meijers, and van Ham 2018; Sassen 2011). This paper aims to make initial contribution to examine the organizational logic of advanced manufacturing cities using empirical data from P.R. China. Specifically, we supplement the traditional macro-level analysis of city rankings with the novel statistical inference method of the weighted stochastic block model to test how the hypothesized industrial network linkages may be observed in reality (WSBM, Aicher, Jacobs, and Clauset 2015).

In this line, the recognition of cities as collections of actors --people and firm agents-- interacting with each other internally and externally is the foundation of the concept of network that is advanced as an alternative paradigm to the traditional urban system theory (Camagni and Capello 2004; Glückler 2007). In their seminal work, Camagni and Capello (2004, p. 496) argue that, for the network to be discerned as a new paradigm that breaks away from traditional spatial facts, "its exact meaning and theoretical economic rationale must be defined and justified, and the novel features of its empirical content need to be clearly identified". In this context, the organization of city-system can assume one of two kinds of city networks, namely a complementarity network or a synergy network. A complementarity urban network entails that the cities not only be specialized in different economic activities, but also partake in spatial economic interactions and hence integration; meanwhile, synergy networks are comprised of similar centers for innovation cooperation to overcome internal know-how weaknesses (Meijers 2005; van Oort, Burger, and Raspe 2010).

Although a voluminous literature has been produced on city networks, some just use the term 'network' to describe interactions or flows within the traditional urban hierarchy. Among those focusing on the actual urban network, research has predominantly been tested empirically by interaction patterns of people and service-based firms. Manufacturing firms are conspicuously absent from city network analysis, in spite of the dramatic transformations this economic sector has experienced over the past decades. Especially, manufacturing firms have been increasingly organized into specialized units with different functions in the production cycle; thus, each functional unit may choose the most appropriate location according to its production inputs of knowledge or skills (Camagni & Capello 2005; Krätke 2014). Such logic of complementarities anchored in specialized and complementary centers steep in the practice of division of labor is here hypothesized to be highly relevant to the structuring of a city network (Glückler and Doreian 2016; van Oort et al. 2010). But more importantly, it has been found that horizontal mergers are common activities in high-tech manufacturing firms in search of innovation in recent years (Haucap, Rasch, and Stiebale 2019). We believe that this micro-level behavior hidden behind the headquarters-subsidiary firm relations would produce the same synergy and cooperation networks in high-tech cities as already evidenced in the case of financial cities. Therefore, in our research, we assume a synergy city network consisting of comparable cities can coexist with a complementarity network as a consequence of the complex organizational logic of high-tech firms.

Therefore, in search of a corroboration of the underlying theory, this research is particularly interested in investigating how such micro-level firm behaviors may interpret the macroscopic spatial behavior of cities. In other words, this study aims to answer two related questions on the economic foundations of urban networks. First, does the city network as a new spatial paradigm really exist, given its specific meaning and the economic rationale that underpins it? Second, if city networks are a reality, what organizational logic regulates how cities interact with each other to produce the observed network behavior of high-tech firms? To contribute to these research questions, the analysis is twofold. First, the study of city rankings of degree centrality constructed on headquarters-subsidiary relationships informs about the existence and macro-level properties of the city network; next, a meso-scale inferential approach of network science is applied to identify complementarity and synergy features of the city networks. As will be explained later, the novel approach of the meso-scale analytical framework can distinguish the connectivity pattern of city groups based on the similarity of intensities in pairwise relations and their associated network structure, such as core-periphery patterns. The paper is structured as follows. First, we review the literature on theoretical frameworks of city networks. Second, we introduce the method of WSBM and the sample data from Chinese high-tech manufacturing firms. Finally, we present and discuss the results of our analyses and conclude the paper with an overview of future research issues.

2.2. The economic foundation of city network

To provide context to our research, we are retracing the history of research on the urban system back to the pre-industrial era. Prior to the Industrial Revolution, an urban system consisted of a hierarchy of urban centers. A city was identified as a monocentric cluster of people and economic activities in the urban center and was clearly separated from the countryside. At the intraurban scale, each center and its rural periphery exchange business goods, services and agricultural products. At the interurban scale, business flows mainly occur within or between urban cores. Also, higher-order centers (known as central places) with a broad range of central functions provide specific functions to lower-order centers. As a result, given the impedance of physical distance, national space is structured to the well-known Löschian honeycomb of market areas (Camagni & Capello 2004; Pacione 2013). For the metropolitan region, the prototype takes the form of a central place system that contains a central city as a core.

With the development of infrastructure, cities shifted their borders and firms became more mobile and flexible. Hence, social and economic activities started to expand into ever-larger geographical areas. Suburban areas emerged as local activity centers, which further leads to the enlargement of cities with multiple centers, or polycentric cities. Metropolitan regions can also lose independent functions in the urban system and transform into parts of an urban network, or polycentric urban region (PUR). In the urban network system, as a result of economic division and specialization, one city can be seen as 'central' for a certain function, while other cities might be the centers for other functions (van Oort et al. 2010).

The city network paradigm is fundamentally built upon two relevant theoretical perspectives. The first is the recognition of cooperation as a successful organizational and behavioral strategy for companies. The model of firm collaboration in technological, commercial, and financial areas is an efficient form to support market potential, innovation and rapid technological change (Lechner and Dowling 2003). The second theoretical perspective is the hypothesis of the city as a collective actor encompassing local firms. Cities are becoming increasingly central both to the movement of goods and related production factors in inter-regional trade. Cities operate on their 'absolute advantage' as they engage in inter-regional trade. In search for competitiveness, firms rely not only on local resources for production, but also progressively on certain advantages and particular assets that cannot be simply achieved through the local market. Thus, firms are inclined to cooperate with other local firms or organizations for the conception and provision of these resources facilitated by regional conditions (Camagni 2002; Camagni & Capello 2004). Therefore, the urban network offers home firms a chance to enlarge their market, as well as enhance the diversity and quality of knowledge, or infrastructure (van Oort et al. 2010).

In line with these two logical blocks, two main types of city networks are proposed based on differences in firm behaviors, namely complementarity networks and synergy networks (Camagni and Capello 2004). A complementarity network is structured under the conditions of cities with similar size but carrying out different functions, thus taking advantage of economies of *vertical integration*, a division of labor and market size (Glückler and Panitz 2016b). In this conceptualization, spatial economic dynamics take place within the scope of the spatial interactions that have commonly been ascribed to cumulative causation. With firms tending to be organized into specialized units, the location of each unit is determined by multiple factors of geographical and historical specificities rather than by a single logic. This specialization pattern is the root cause of linkages between units, and therefore for an economic relationship between cities, especially in manufacturing (Camagni and Capello 2004; van Oort et al. 2010).

The goals of a synergy network are for the economies of *horizontal integration* and network externalities when innovation and the control of innovation assets are critical for firms. It could be described as the interactions among cities operating similar functions. In particular, firms may overcome critical technological and informational shortages no matter where they are located through the cooperation, which is not allowed in the traditional model. Examples can be found in the network of financial centers of higher order and in the interactions among cities performing headquarter and advanced services functions (Camagni et al. 2013; Sassen 2011). However, as innovation is a crucial function in high-tech manufacturing, horizontal mergers of firms in the same industry have been commonly observed when two firms look for economies of scale and innovation opportunities (Haucap et al. 2019). As a consequence, if a firm's goal is to reach a higher level of innovation and establish a parent-subsidiary relation with another firm through merger, then such firm relation at the micro level could also lead to the similar macro spatial behavior as synergy network in high-tech manufacturing.

A large volume of empirical research has tested the spatial structure of city networks, such as the movement of people among global cities (Smith and Timberlake 2001) as well as at more regional scales (Burger, Meijers, and Van Oort 2014; Neal 2012). Along this line, studies in China have mainly focused on the regional level, such as Yangtze River Delta region (Luo, He, and Di 2011) and selected major cities (Liu, Derudder, and Wu 2016; Wen and Thill 2016). When it comes to the organizational interactions of firms and establishments, research has concentrated on advanced producer services in the world city network (WCN) (Taylor 2001, 2004) and the global production network (GPN) (Coe, Dicken, and Hess 2008; Glückler and Panitz 2016a; Henderson, Dicken, and Hess 2002). Despite the broad consensus on the concept of urban network and economic complementarities from both the academic literature and the policy arena, few empirical studies have assessed the fitness of theoretical urban network models in real contemporary urban systems (van Oort et al. 2010).

The empirical assessment of national urban systems is more often conducted in European countries and China, with only a few in the U.S. (Glaeser, Ponzetto, and Zou 2016; Neal 2011). Following the tradition of WCN research, most of these studies emphasize the interactions of producer service firms (Pan et al. 2017; Rozenblat 2015). Only a small group of scholars have used the relationship between parent and subsidiary firms (multinational or listed firms) to study the properties of the urban network globally (Alderson, Beckfield, and Sprague-jones 2010; Rozenblat 2010) or regionally (Li 2014; Rozenblat and Pumain 2007). Meanwhile, the concept of the city network grounded on the behavior of manufacturing firms has seldom been examined in reality (Krätke 2014; van Oort et al. 2010), in spite of the great dynamism of this industrial sector and its leading role on other economic sectors. Specifically, it has been pointed out that the spatial pattern of manufacturing firms in China is characterized by a broad distribution across various cities of different sizes in the network rather than by a concentration in a few urban centers (Brakman, Garretsen, and Zhao 2017). Moreover, the complex behavior of high-tech manufacturing firms under the global economy presents a great opportunity to test its impact on the macro-level spatial logic of cities. Hence, this research aims to stimulate more discussion on economic complementarities and synergy in urban networks.

2.3. Conceptualization of meso-scale structure of urban network

With the objective to better understand the organizational logic of city network in China's high-tech manufacturing cities, we supplement the distributional analysis of network degree centrality with a meso-scale analytical perspective to study the structures exhibited by the network at a granularity between the local (node level) and the global (network as a whole). This approach has recently been proposed and validated for the analysis of meso-scale structures in WCN by Zhang and Thill (2019). In the latter study, a new analytical framework relying on WSBM is empirically investigated to infer latent meso-scale structures among 126 world cities based on undirected Internet discourse data flows; the results clearly indicate that there is a multiple core-periphery hybrid structure in these 126 world cities. When industrial structures are concerned, information asymmetry is an important property so that directionality is critical in unraveling network logic. Therefore, in this research, given the methodological advantages of the meso-scale analytical framework, we extend it to the study of directed industrial relations between cities to isolate meso-scale structures and quantify and evaluate the organizational logic in a national city system.

Under the conceptualization of meso-scale structures, the city network structure can be depicted by a schematic block connectivity matrix (Figure 2.1), where each block contains the stochastically equivalent cities indicating equivalent roles in generating group relations with others. At least six types of network organizations can be hypothesized. The first one is a community structure sensu stricto, with dense interactions within each group (dark blocks in Fig. 2.1-A), while weak connections (white blocks) exist with other groups. Regionalization in national urban systems fits this structure. The second meso-structure is called a core-periphery (CP) hierarchy (Fig. 2.1-B) that consists of the core group(s) and edge groups. In this structure, strong connections exist not only within the core but also with their peripheries, whereas there is weak interaction between peripheries. The CP structure has often been identified as the dominant organizational logic in world city networks. Unlike the qualitative angle that uses the ranking technique to differentiate the cores in the network, this approach obtains the CP structure based on statistics and probability theory that a specific structure is generated from statistical inference. Cities in core groups can be classified into alpha, beta, and gamma cores, which differ by their connection strength. Third, the random network (Fig. 2.1-C) shows no significant relations among groups and operates as a 'flat world' in a sense. This structure could be achieved with the ubiquitous improvements of connectivity and cooperation among nodes across the network. The fourth one is a disassortative community structure with strong links between groups and weak interactions within each group. This structure may be present in a two-mode network. Lastly, Figures 2.1-E and 2.1-F depict two hybrid structures that represent more complex and denser city networks, such as the web-based world city network in Zhang and Thill's recent findings.

In a directed network, the off-diagonal blocks inform about the power relations of command and operation among cities. This method of meso-scale structures offers several advantages when it is applied to examine hypothesized organizational logics. First, it provides a more comprehensive understanding of latent connectivity (e.g. CP hierarchies, or hybrid CP structures) in addition to the traditional macro-scale analysis. Second, the probability-based WSBM enables us to identify the relation in each city pair and return the connection strength based on the arc weights. As a result, it disentangles the network by isolating meso-scale structures based on the strength of intra- and inter-group connections. One can compare city pairs with a heat map, and from there, interpret the structure of intercity relations. Specifically, a complementary relation can be traced by a meso-structure comprised of core(s) exhibiting control order and peripheries with lower-order function. A community structure with strong intra-group connection operating multiple functions would be indicative of a synergy network. Given the conceptual arguments advanced earlier, an integrated national CP structure with regional communities (Fig. 2.1-F) is expected to fit well the manufacturing city structure presented in our empirical analysis.

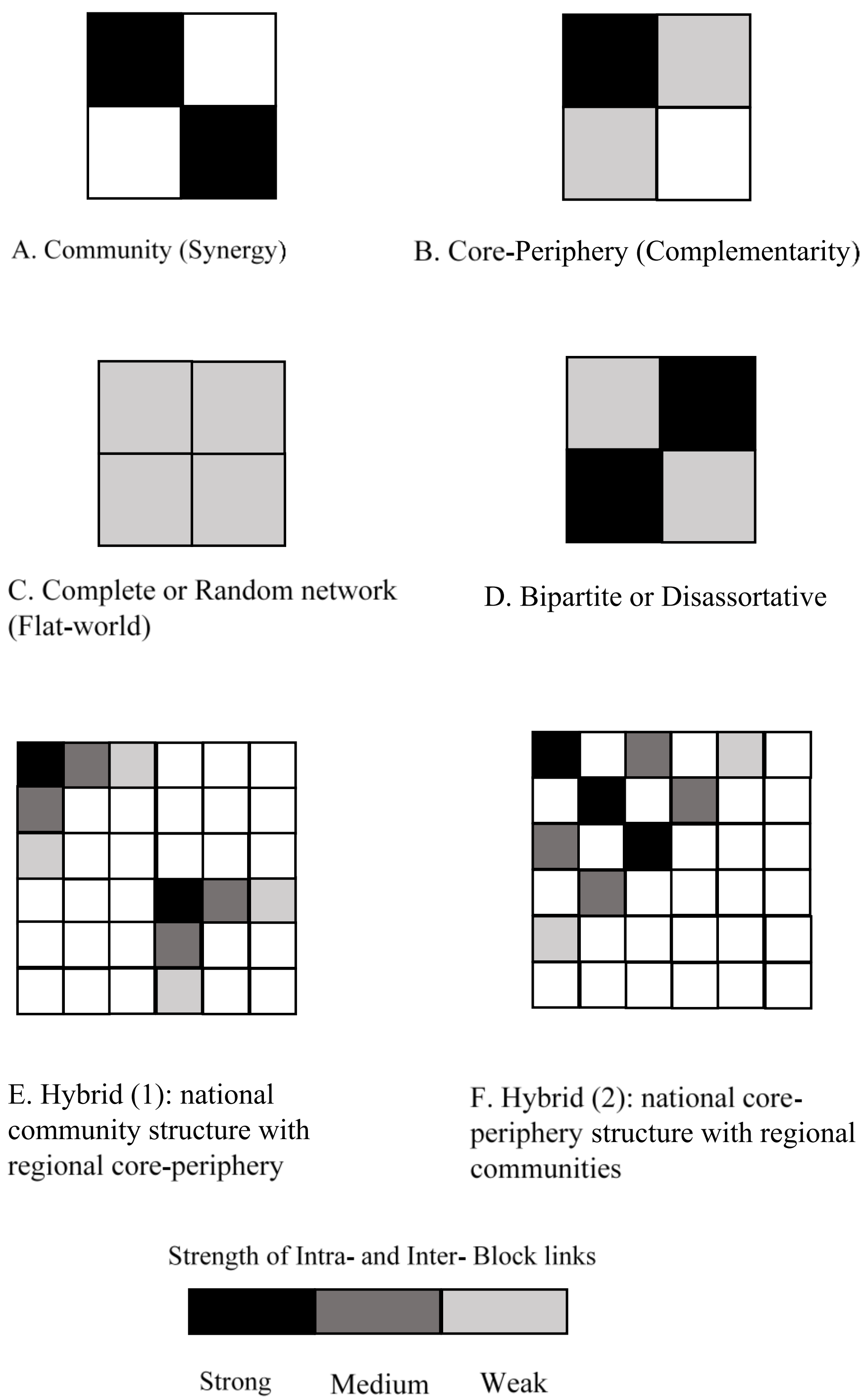


Figure 2.1: Hypothetical meso-scale network structures (After Zhang and Thill, 2019)

Many methods and algorithms have been proposed to detect meso-scale structures in network analysis, ranging from the early k-cores technique with pre-assumed threshold to algorithmic community detection. Among them, a lot of work has been sparked by the property of modularity in complex systems (Newman 2006; Newman and Girvan 2004), such as the Louvain clustering algorithm (Blondel et al. 2008) and Infomap measures (Rosvall and Bergstrom 2008). The former algorithm is a hierarchical clustering approach based on the modularity measure that provides an effective partition of the network. One expects that the partition groups are more densely connected to each other than a statistically null model. In contrast to modularity maximization, the approach of Infomap basically rests on flow-based detection that designs to assess the clustering quality. The cluster is generated by single meta-nodes with similar dynamical function through the process aggregating blocks of nodes (Held, Krause, and Kruse 2016; Peel, Larremore, and Clauset 2017). Although these approaches are popular, there is a common shortcoming that a certain structure must be presumed beforehand (e.g., either community or core-periphery), thus leading to overlook the possibility of other meso-scale structures (Zhang and Thill 2019).

In order to identify the structure, one of the most popular techniques in network science is the stochastic block models (SBMs) (Holland, Laskey, and Leinhardt 1983; Nowicki and Snijders 2001; Peel et al. 2017). Recently, the introduction of weighted SBM in network structure analysis displays several advantages over others. First, this model specifies a natural solution to the challenge of unweighted edges in SBMs to learn from both edge presence and weight information. More importantly, as sparse network is a common feature in real-world networks --only $O(n)$ pairs of connections may have weight--, WSBM is well suited as it is formulated to incorporate sparse networks within the model. Finally, the performance of the WSBM from empirical work has been found superior to other methods focusing on edge-weight prediction without pre-assuming group numbers. The WSBM is described as a natural generalization of the well-known SBM to edge-weighted sparse networks with a statistically principled resolution; it also removes the prerequisite of any thresholds. Thus, this model can be chosen to discover the latent group structures in a broader range of systems (Aicher et al. 2015).

2.4. Model and data

2.4.1. Weighted Stochastic Block Model

WSBM is built upon the stochastic block model (SBM) and the exponential family of probability distributions, and further generalizes the SBM to weighted networks. In the SBM, there is an adjacency matrix *A* with binary values of edges that represent the city network relations, i.e., $A_{ij} \in \{0,1\}$. This network is decomposed into a fixed number of latent groups, *K;* vector $z \in \{1,..,K\}$ indicates the group label of city nodes. The number *K* of potential groups determines the complexity of the model. At variance with several other techniques, the approach for choosing *K* is based on Bayes factors that select the number of groups with the largest marginal log-likelihood. Each possible group is assigned a vector *z* to represent group membership. Then, given each pair of groups (*kk'*), the SBM assigns an edge existence parameter to each edge bundle $\theta_{kk'}$. For example, the edge existence parameter for each interaction (i.e., relation) observed between cities in group *i* and group *j* respectively is $\theta_{z_i z_j}$. The existence probability of the edge parameter $\theta_{z_i z_j}$ only depends on the group memberships of cities *i* and *j*. Thus, given a city network with any latent grouping *z* and stochastic block matrix θ, the SBM's likelihood function is

$$\Pr(A|z,\theta) = \prod_{ij} \theta_{z_i z_j}^{A_{ij}} \left(1 - \theta_{z_i z_j}\right)^{1-A_{ij}} . \tag{2.1}$$

Thus, the likelihood function takes the form of the exponential family of probability distributions

$$\Pr(A|z,\theta) \propto \exp\left(\sum_{ij} T(A_{ij}) * \eta\left(\theta_{z_i z_j}\right)\right)$$

(2.2)

where $T(x) = (x, 1)$ is the sufficient statistic of the Bernoulli random variable with vector value and $\eta(x) = (log[x/(1\text{-}x)], log[1\text{-}x])$ are its natural parameters with vector values consistent with parametric distributions belonging to the exponential family. By choosing a different pair of functions (T, η) demarcated two domains χ and x, a stochastic block model can be generalized with weights drawn from an exponential family distribution over χ.

In WSBM, each edge parameter θ_{zi*zj} specifies a weight with distribution drawn from the exponential family (T, η), including the normal, exponential, Pareto, and Poisson distributions. The group structure of the WSBM adopts the same stochastic equivalence principle as the classic SBM. In other words, all cities in one group share the same probabilistic connectivity to all other groups.

For example, given an observed city network C and a range of group numbers K, the edge weights are real-valued χ = R. We can choose to model the edge weights applying the normal distribution. This distribution has sufficient statistic $T=(x, x^2, 1)$ and natural parameters $\eta = (\mu/\sigma^2, -1/(2\sigma^2), -\mu^2/(2\sigma^2))$; as a result, each edge bundle $(z_i z_j)$ is parameterized by a mean and variance $\theta_{zi*zj}=(\mu_{z_i z_j}, {\sigma^2}_{z_i z_j})$. Finally, the likelihood function would be

$$\Pr(A|z,\mu,\sigma^2) = \prod_{ij} \mathrm{N}\left(A_{ij}\middle|\mu_{z_i z_j}, \sigma^2_{z_i z_j}\right) = \prod_{ij} \exp\left(A_{ij} * \frac{\mu_{z_i z_j}}{\sigma^2_{z_i z_j}} - A_{ij}^2 * \frac{1}{2\sigma^2_{z_i z_j}} - 1 * \frac{\mu^2_{z_i z_j}}{\sigma^2_{z_i z_j}}\right). \quad (2.3)$$

This construction uses a normal distribution to model the values of observed edge bundles. To obtain the group structure, the optimization of the likelihood function with z and θ is required. Aicher et al. (2015) apply a Bayesian approach to maximize the likelihood by considering z and θ

as random variables with the prior distribution $P(z, \theta)$. Given a Bayesian framework, the posterior distribution is

$$P(z,\theta|A) \propto P(A|z,\theta)\, P(z,\theta). \tag{2.4}$$

Furthermore, an algorithm on variational Bayesian inference (Aicher et al. 2015) is created for the purpose of maximization of the expected log-likelihood, so that WSBM can be used to produce the parameters z and θ with different values of likelihood. In general, WSBM provides a statistical inference method to detect the meso-scale structure of a network. It allows us to find the latent groups of nodes that offer the best fit for any observed network, which is particularly beneficial to the study of networks with weighted edges. This study uses Matlab 2016b to run the analysis of WSBM and Gephi for visualization.

2.4.2. Data

The dataset used in this study has been drawn from the China Non-listed Enterprise Database (1998-2008). This database is administered by GTA Company and collected from the National Bureau of Statistics of China. It covers all non-listed manufacturing firms with annual sales over five million Yuan (around $600,000 at the exchange rate of 2000). It provides firm-level data on firm structure and operation, such as ownership, location, and capital structure, profits, and product categories. More importantly, each firm in this dataset is assigned a single 4-digit Standard Industrial Classification (SIC) code according to its main products, which allows us to identify the sub-sectors of high-tech manufacturing that best match the firms and their production activities. Although firms with sales under 5 million Yuan were not surveyed, there is no loss of generalizability as it has been documented that manufacturing firms (listed and non-listed) over that size generate 90% of industrial output of China and 98% of total exports (Zhu, He, and Luo 2019). The following descriptive analysis is based on the enterprises above the designated size.

In 2008, the database includes 411,821 non-listed firms (or establishments) that accounted for around 97% of all manufacturing firms according to the National Bureau of Statistics of China. Firms (either listed or non-listed) can be differentiated on the basis of ownership modalities into state-owned enterprises (SOEs), foreign-owned enterprises (FOEs), and privately-owned enterprises (POEs) (Zhu et al. 2019). Given our research purpose, SOEs are excluded from the analysis. Only POEs and FOEs are considered hereafter since our research assumes that the locational behavior of a firm is determined by the market, rather than by national strategy or local governments (Guo, He, and Li 2015).

Data on high-tech POEs and FOEs are further retrieved based on their 4-digit industry code. According to the manufacturing classification of OECD (2011), four sub-sectors can be identified as high-tech manufacturing: pharmaceuticals and biotech; office and computing machinery; radio, TV and communications equipment; as well as medical equipment, precision, and optical instruments. Then, we first apply the above high-tech industry classification to our dataset and sort out the firms that belong to each of the computing machinery, technology hardware and equipment, pharmaceuticals, and biotech sub-sectors. Second, the between-city relational data of corporate headquarters and subsidiaries are built from their respective city locations. For domestic POEs, we directly assemble corporate affiliations to detect firm's hierarchy – such as headquarters, divisions, subsidiaries, affiliates, and joint ventures – and on where they are located. However, for FOEs, we use the position of regional corporate centers in China to present the highest order of corporate function, and FOEs also include enterprises from the region of Hong Kong, Taiwan, and Macao according to the National Bureau of Statistics.

After identifying the connections between subsidiaries and their headquarters, the geographies of these firms are aggregated into the city level for the sake of network analysis shaped by the different industrial sectors. Specifically, in our directed network, a node in the network matrix is a city with headquarters and/or subsidiaries of high-tech firms. Each edge represents an ownership relationship implying a locational choice. Head offices in city A that choose city B as their locations of subsidiaries send an arc toward city B. The weight of each arc denotes the number of subsidiaries for each city dyad. Taking firms in Beijing and Tianjin as an example, there are five headquarters in Beijing and each one located one manufacturing subsidiary in Tianjin; then the weight on the Beijing-to-Tianjin edge is 5.

Overall, in 2008, there are 1,419 firms in the sector of office and computing machinery; 172 (12.1%) firms are subsidiaries of domestic enterprises or foreign enterprises with a regional business center in China, and they are distributed in 25 cities. For the sector of technology hardware and equipment, there are 9,548 firms, and 631 (6.6%) are subsidiaries, including 312 domestic and 319 foreign subsidiaries with regional headquarters in China. Finally, 4,548 firms operate in the sector of pharmaceuticals and biotech; 618 (13.6%) subsidiaries are considered for network analysis (Table 2.1). The matrices for the three sectors containing different sets of nodes, edges, and weights not only can be used for standard network analysis, such as degree centrality, but more important for the meso-scale city structures shaped by firms and their subsidiaries.

Table 2.1: Summary information on high-tech manufacturing firms for city network analysis

Sub-sector	No. of firms	No. of domestic subsidiaries	No. of foreign subsidiaries	City matrix
Computing machinery	1,419	50	122	25×25
Technology hardware and equipment	9,548	312	319	76×76
Pharmaceuticals and biotech	4,548	400	218	111×111

2.5. Analytical results

2.5.1. City ranking and distributions

We start with results of the macro-level analysis of city rankings for the three industrial sectors of interest. In detail, the study differentiates between the role of urban regions as control centers of corporate ownership (a city's out-degree centrality) and their role as a place of subsidiary business activities (a city's in-degree centrality). This is significant for the understanding of city networks as conduits of territorial organization by taking into account the direction of inter-city links. On the one hand, cities with a high out-degree centrality can be interpreted as exerting strong control over others, such as command over capital flows. On the other hand, cities with high in-degree centrality stand out by attracting inward flows. The in-degree measurement also reveals a city's platform function (Krätke 2014). This function allows firms to utilize the local production advantage, or access to specific information and resources, especially in the case of investments entering into foreign markets.

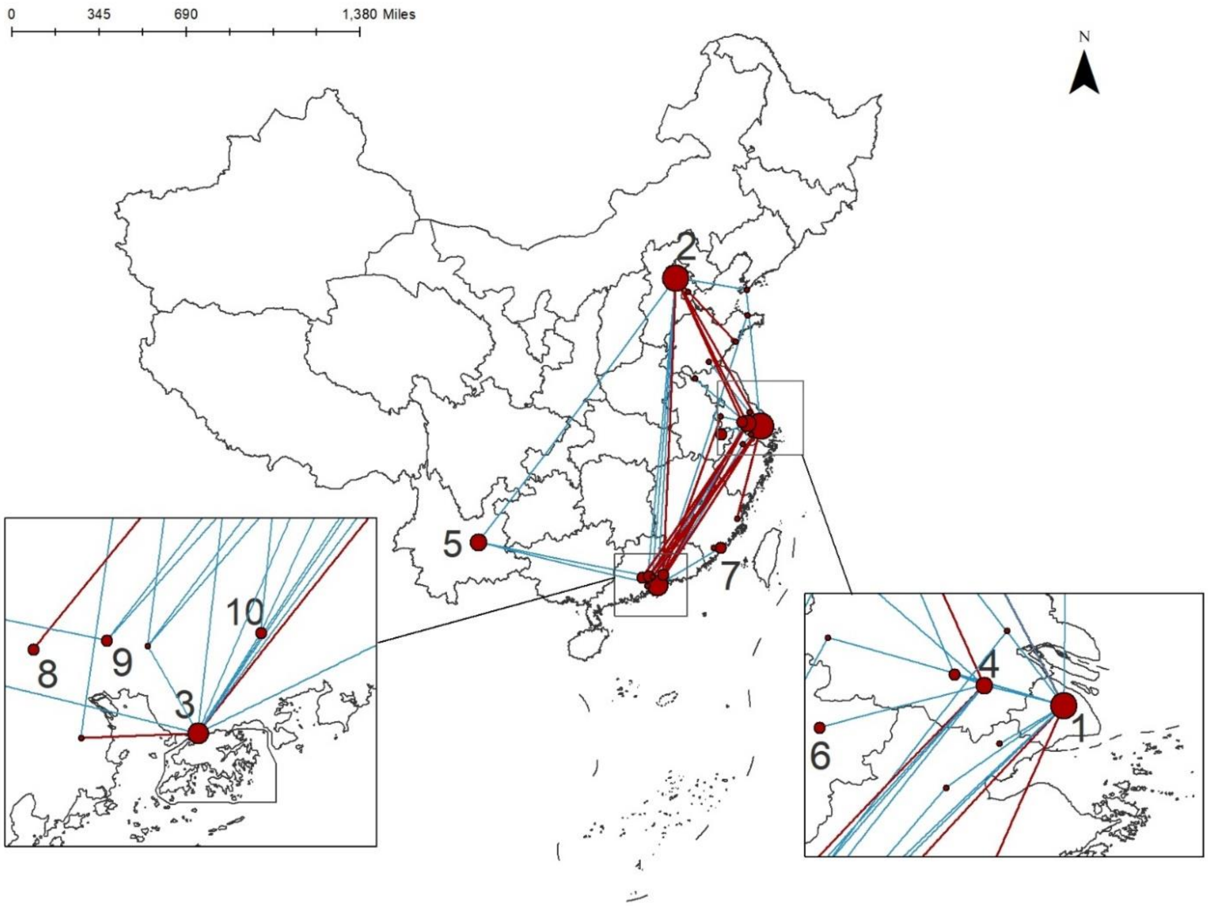
The results indicate that city networks do in fact exist with regard to the three high-tech sectors in China. Figures 2.2, 2.4, and 2.6 illustrate the geographic distribution of city nodes and city dyads of the respective industries in China. The size of markers denotes the magnitude of out-degree centrality of cities with consideration of edge weights. Given the state of industry development in 2008, it is not a surprise that firms from the three sub-sectors are primarily concentrated in fast growing cities in the East Coast region, and thus this is also where the dyadic edges with higher weight are. One can describe cities with dense network links as superior centers of industry on a national scale. The ranking based on degree centrality introduces the nodal centralities of cities involved in the city networks of the different sub-sectors.

In the sector of office and computing machinery (Fig. 2.2-2.3), firms are confined to a comparatively small and selective geographical territory in 2008 encompassing 25 cities, of which 17 belong to the regions of the Yangtze River Delta and of the Pearl River Delta. The in-degrees and out-degrees (Table 2.2) expose the distinction between control and attraction power. Shanghai, Beijing, and Shenzhen are the top three cities in terms of control capacity (out-degrees of 30, 23, and 13, respectively), while Suzhou, Shenzhen, and Shanghai show prominently as target city nodes in this network. Although Suzhou contains a large number of computing machinery firms, the number of headquarters based in the city is much smaller according to its out-degree centrality; hence, Suzhou features as a subsidiary center. From the value of out-degrees and the distribution of city dyads, one can also garner that Top-3 cities (Shanghai, Beijing, and Shenzhen) not only contain the majority of parent companies, but also comprise strong mutual parent-subsidiary relationships, which is evidenced by the top-20 city dyads depicted in Fig. 2.2. Furthermore, the uneven distribution of firms across the network is also noted in statistical distributions of between-city weights reported across headquarter city nodes and across city dyads (Fig. 2.3). About 50% of weights are concentrated on 20% of city nodes and on about 20% of city dyads.

In the sector of radio, TV and communications equipment (Fig. 2.4), Shanghai, Shenzhen, and Beijing once again demonstrate active command and control capabilities; in fact, their out-degree values are disproportionately large (98 to 72), while the rest of out-degrees is under 20 (Table 2.3). Six out of the top-10 controlling cities are the same as for the sector of computing machinery, although with slightly different rankings. Moreover, 40% of city nodes account for about 75% of edge weights (Fig. 2.5), and they concentrate on about 45% of city dyads. On the other hand, Suzhou, Shenzhen, and Dongguan show the best performance of attracting corporate interests from other cities and feature as the top subsidiary cities.

The pharmaceutical and biotech sector (Fig. 2.6) shows some similarities with the other two sectors, but also striking differences. For instance, Beijing and Shanghai are once again among the cities with the most corporate headquarters (out-degrees of 35 in Table 2.4 left). They are joined by Hangzhou to form the Top-3 cluster of leading centers of control in China. The rest of the top ten cities for this sector exhibits notably greater geographic diversity, with several cities from the western regions, such as Xi'an, Chengdu and Chongqing, and cities from the northeast, like Jilin. As subsidiary centers, Chengdu and Shanghai with in-degree of 7, and Beijing, Guangzhou and Suzhou (all with in-degree of 6) stand out. However, this only weakly reflects their attracting capabilities in this particular subsector as other cities are not trailing far behind. In fact and along the same line, from the distribution of between-city weights across city nodes and city dyads, we find that the edge weights (Fig. 2.7) do not show the clumping that was so striking in the other two high-tech sectors (Fig. 2.3 & 2.5).

The macro-level analysis of city rankings leads to three main conclusions. First, the cities of Shanghai, Beijing and Shenzhen consistently exhibit the highest level of command and control over the rest of China's city network across high-tech industries. This is evidenced by the high degree of connectivity of these cities in all three high-tech subsectors of manufacturing industries as well as by the strong relationships that exist between parent firms in one city and subsidiaries in a different city. These cities have a super-gravitational effect for all three sectors, especially for computing machinery and communications equipment firms. Second, the location choice of headquarters of high-tech manufacturing firms presents a strong preference for large cities with diversified economies. Small and medium sized cities with specialized industrial structures are better described by their production function, sometimes in a rather pronounced way, such as in the case of computing machinery in Suzhou, technology hardware and equipment in Dongguan, or pharmaceuticals and biotech in Xi'an. These features of industrial locations restate the significance of traditional principles of 'urbanization economies' and 'specialized economies'. Third, at the regional level, cities from the Pearl River Delta and the Yangtze River Delta have dense inter-regional as well as intra-regional interdependencies. Beijing, as the core of the Jing-Jin-Ji region (Beijing-Tianjin-Hebei metropolitan region), barely exhibits any business interactions within the confined of the region, whereas it has a number of robust linkages with distant cities from the two Delta regions. This raises the question of the detailed nature of interdependencies across city networks for different industrial sectors. We will rely on WSBM to further the analysis of city network structures.



Note: Numbers refer to city names from Table 2.2 (left).

City Nodes (Size varies by out-degree centrality)

Top-20 City Dyads

20-45 City Dyads

Figure 2.2: Geographical distribution of cities and city-dyads by office and computing machinery firms

Table 2.2: City ranking by out-degree (left) and in-degree (right) centrality by office and computing machinery firms

City ranking by out-degree centrality: Top-10 cities (degree unit: number of headquarters)

City name	Out-degree
1 Shanghai	30
2 Beijing	23
3 Shenzhen	13
4 Suzhou	5
5 Kunming	4
6 Xuancheng	2
7 Xiamen	2
8 Foshan	1
9 Guangzhou	1
10 Huizhou	1

City ranking by in-degree centrality: Top-10 cities (degree unit: number of subsidiaries)

City name	In-degree
1 Suzhou	23
2 Shenzhen	12
3 Shanghai	6
4 Dongguan	6
5 Beijing	4
6 Wuxi	4
7 Nantong	3
8 Guangzhou	2
9 Huizhou	2
10 Nanjing	2

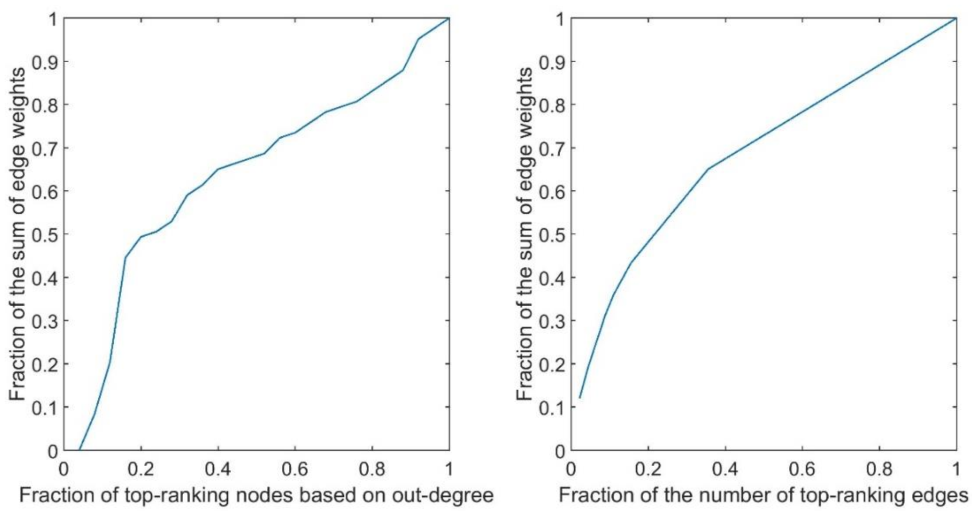
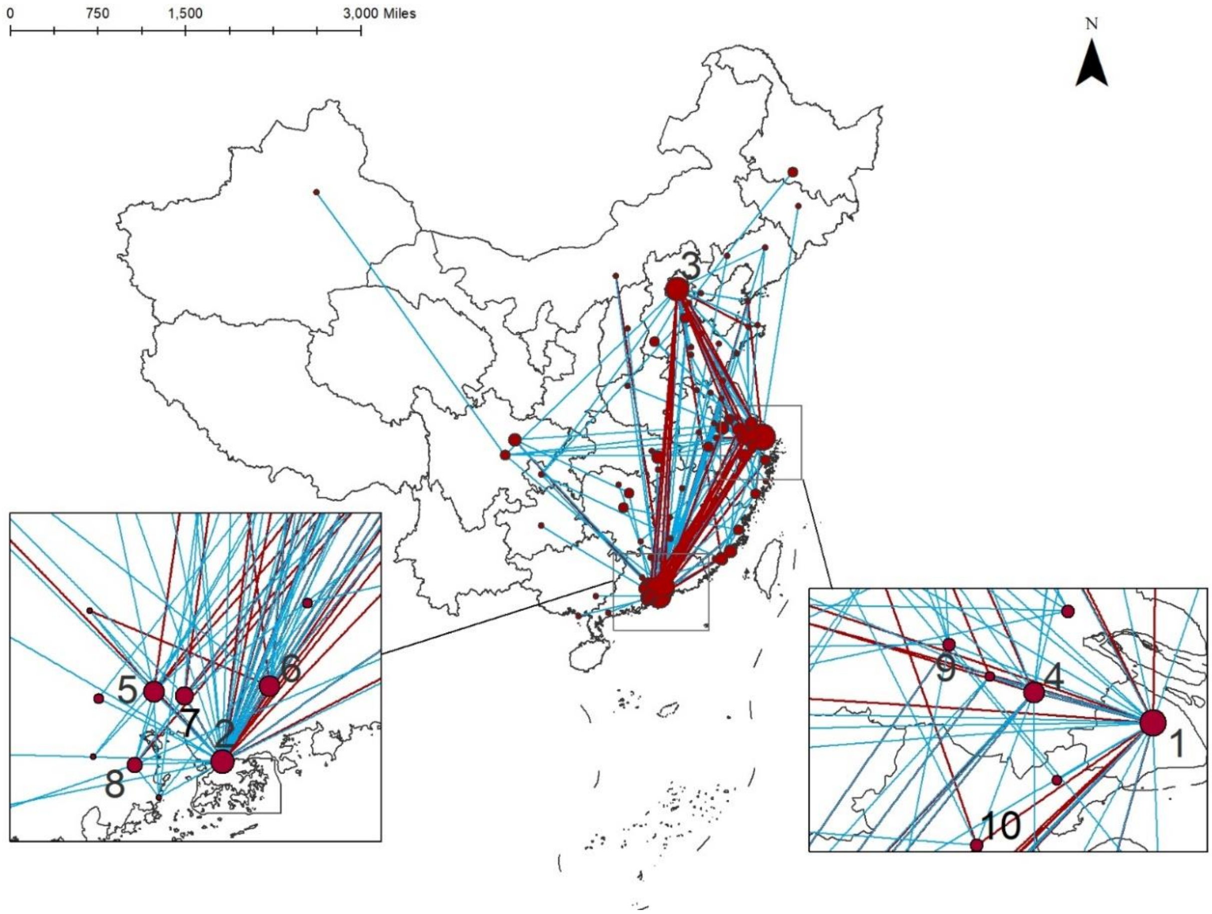


Figure 2.3: Distribution of between-city weights across city nodes (left) and across city dyads (right) by office and computing machinery firms



Note: Numbers refer to city names from Table 2.3 (left).

City Nodes (Size varies by out-degree centrality)

Top-30 City Dyads

31-180 City Dyads

Figure 2.4: Geographical distribution of cities and city-dyads by technology hardware and equipment firms

Table 2.3: City ranking by out-degree (left) and in-degree (right) centrality by communications equipment firms

City ranking by out-degree centrality: Top-10 cities (degree unit: number of headquarters)

City name	Out-degree
1 Shanghai	98
2 Shenzhen	78
3 Beijing	72
4 Suzhou	17
5 Guangzhou	14
6 Huizhou	13
7 Dongguan	8
8 Zhongshan	7
9 Changzhou	5
10 Hangzhou	4

City ranking by in-degree centrality: Top-10 cities (degree unit: number of subsidiaries)

City name	In-degree
1 Suzhou	61
2 Shenzhen	37
3 Dongguan	25
4 Wuxi	22
5 Shanghai	19
6 Tianjin	12
7 Hangzhou	11
8 Huizhou	11
9 Beijing	8
10 Guangzhou	7

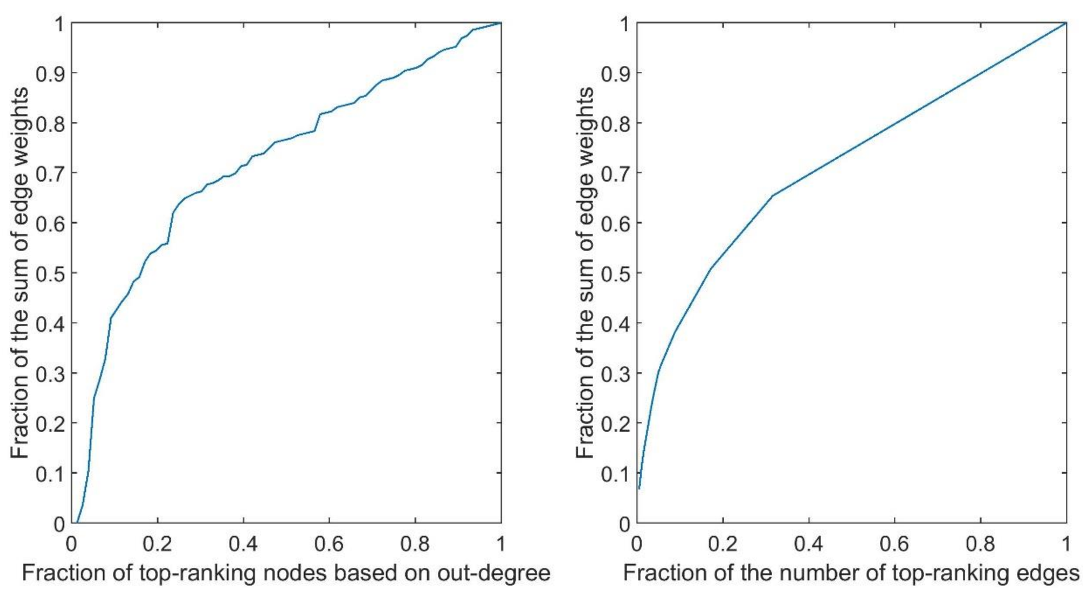
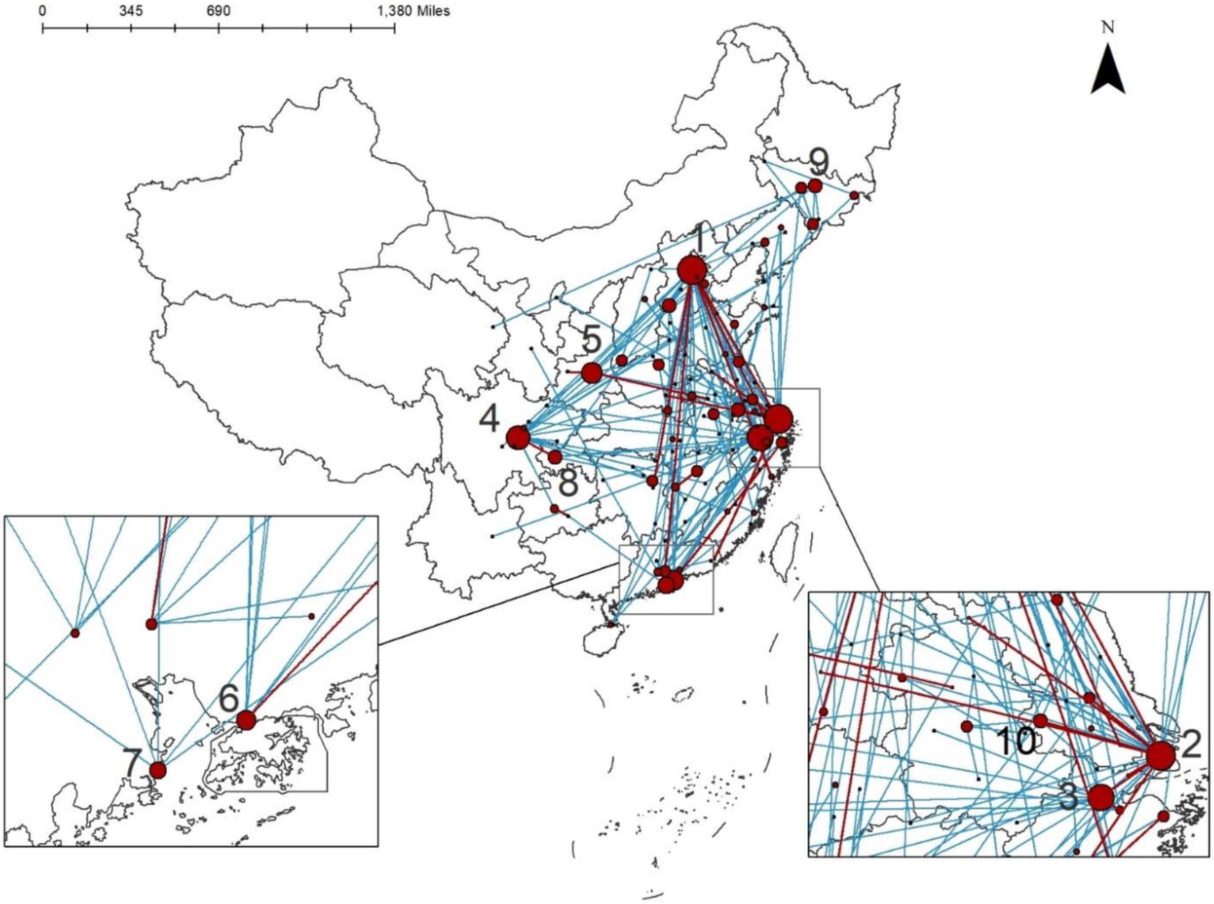


Figure 2.5: Distribution of between-city weights across city nodes (left) and across city dyads (right) by technology hardware and equipment firms



Note: Numbers refer to city names from Table 2.4 (left).

City Nodes (Size varies by out-degree centrality)

Top-20 City Dyads

21-170 City Dyads

Figure 2.6: Geographical distribution of cities and city-dyads by pharmaceuticals and biotech firms

Table 2.4: City ranking by out-degree (left) and in-degree (right) centrality by pharmaceuticals and biotech firms

City ranking by out-degree centrality: Top-10 cities (degree unit: number of headquarters)

City name	Out-degree
1 Beijing	35
2 Shanghai	35
3 Hangzhou	14
4 Chengdu	11
5 Xi'an	7
6 Shenzhen	6
7 Zhuhai	5
8 Chongqing	4
9 Jilin	4
10 Nanjing	4

City ranking by in-degree centrality: Top-10 cities (degree unit: number of subsidiaries)

City name	In-degree
1 Chengdu	7
2 Shanghai	7
3 Beijing	6
4 Guangzhou	6
5 Suzhou	6
6 Shaoxing	6
7 Hangzhou	4
8 Bozhou	4
9 Dalian	3
10 Nanchang	3

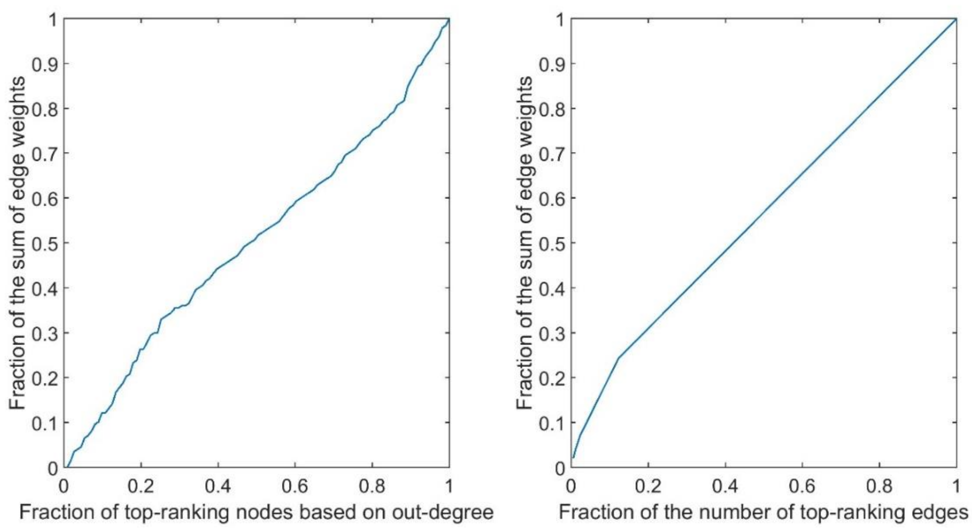


Figure 2.7: Distribution of between-city weights across city nodes (left) and across city dyads (right) by pharmaceuticals and biotech firms

2.5.2. Meso-scale structure detection

The second part of this study is to identify the network structure and city partitions by industry sector from a meso-scale perspective taking direction into account. This section deals with the power and direction of specific inter-city interactions in three subsectors of manufacturing firms and visualizes properties of the network structure at the meso-scale level. Unlike the city ranking analysis, the advantages of considering meso-scale structures are that this approach offers us a more comprehensive depiction of the channels of inter-city linkages in the network based on the magnitude of their centrality with arc weights. It defines city groups according to their positions in the network, thus underscoring the organizational logic created by the interdependencies of a particular interaction. In practice, the best-fit WSBM is determined by the value of maximum log-likelihood with the number K of city groups allowed to range from 3 to 10. Given the different distributional properties of centrality values and edge weights in the three industrial sectors, the optimal number of city partitions is anticipated to be different as well.

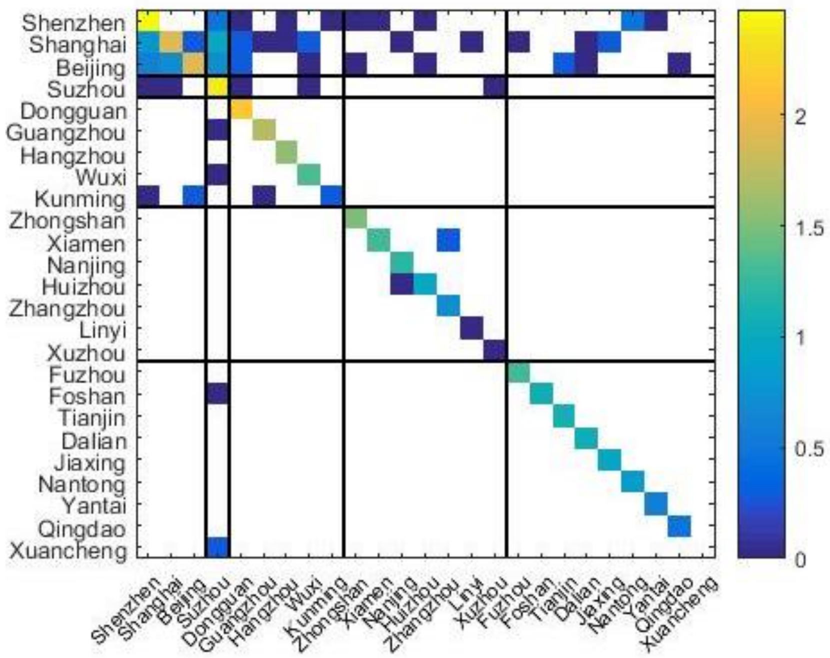


Figure 2.8: Heat map of city-based connectivity matrix formed by office and computing machinery firms (Colored by Log of edge weights)

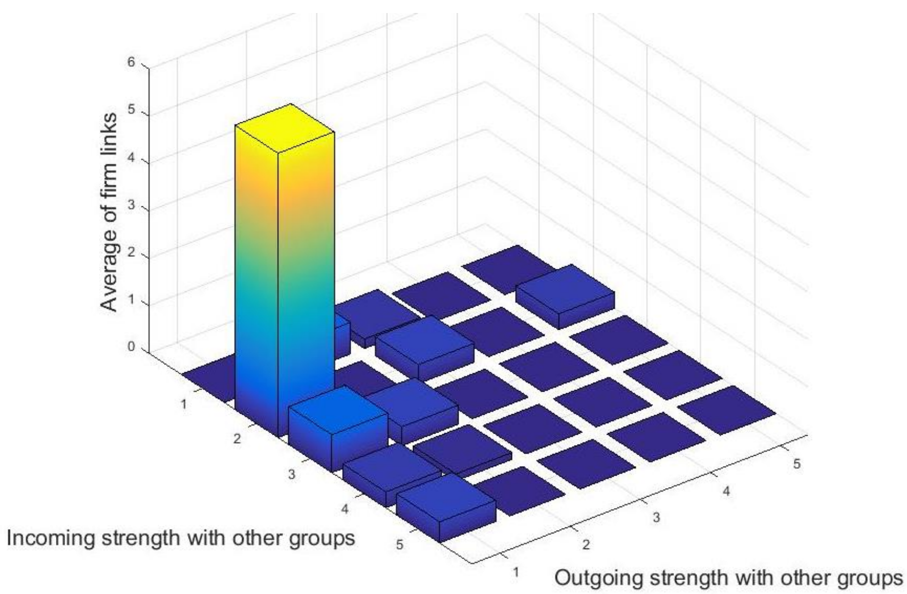


Figure 2.9: 3D block matrix of Meso-scale structure in city network formed by office and computing machinery firms

For the office and computing machinery sector, the Chinese cities are optimally partitioned into five groups according to the maximum likelihood criterion. The heat map of the pairwise city-based connectivity matrix (25 cities included) of computing machinery activities (Fig. 2.8) depicts directed city groups ordered on the magnitude of out-degree centrality of cities. The relation between city A on the Y-axis and city B on the X-axis represents that there are headquarters in city A and their branches are located in city B. Each pair of cities can be located on one of the blocks with headquarter and subsidiary relations. The diagonal refers to the total number of firms from this sector in each city. Colored cells correspond to connection strength, whereas clear cells correspond to the absence of links between cities in this dyad. For example, in Figure 2.8, headquarters from Shenzhen mainly locate their branches in Suzhou and Nantong according to the connection strength, and the remaining cities are Dongguan, Hangzhou, Kunming, Zhongshan, Xiamen, Huizhou, and Yantai.

Given the schematic meso-scale structures that may manifest themselves (Fig. 2.1), the WSBM suggests the existence of a multiple core-periphery (CP) urban system. More specifically, the first group, which also performs as the dominant core, contains three cities: Shenzhen, Shanghai, and Beijing. The higher order of functions of these three cities is not only supported by a large number of intra-group linkages but also dense business interactions with other groups, which is a signature feature of the core group. A single city constitutes the second partition and that is Suzhou city. Suzhou possesses a rather weak core function that includes a large number of production plants but limited corporate headquarters controlling firms established outside of the city. The three remaining city groups are considered as peripheries or semi-peripheries specialized in production activities. Figure 2.9 depicts a generalized block matrix of the city network with five city groups as nodes; it shows a strong connectivity between the two cores whereas the other blocks are very loosely connected.

As can be seen from the 3D chart, there are over 4 times as many links between groups one and two as between any other groups. While all the cities in the last three groups are peripheries of core groups, some cities still stand out. Headquarters in Kunming locate production plants in the core cities of Shenzhen and Beijing; Foshan and Xuancheng (group 5) choose Suzhou as the location of their subsidiaries. As most firms select big cities as control centers, parent corporations originated from small cities also locate their plants in the core regions. This finding corroborates the hypothesis that cities and territories behave like collective actors in the city network paradigm (Camagni and Capello 2004). Cities with limited local resources resort to connecting to other cities to access these resources. Detailed partition results are given in the form of a color-coded network in Figure 2.14. In this figure, the five groups of cities are assigned different colors and the sizes of city nodes and labels represent the order of weighted out-degree centralities. The width of each edge between a pair of cities illustrates their connection strength. A color-coded table with group numbers and city names is listed below the network for convenience.

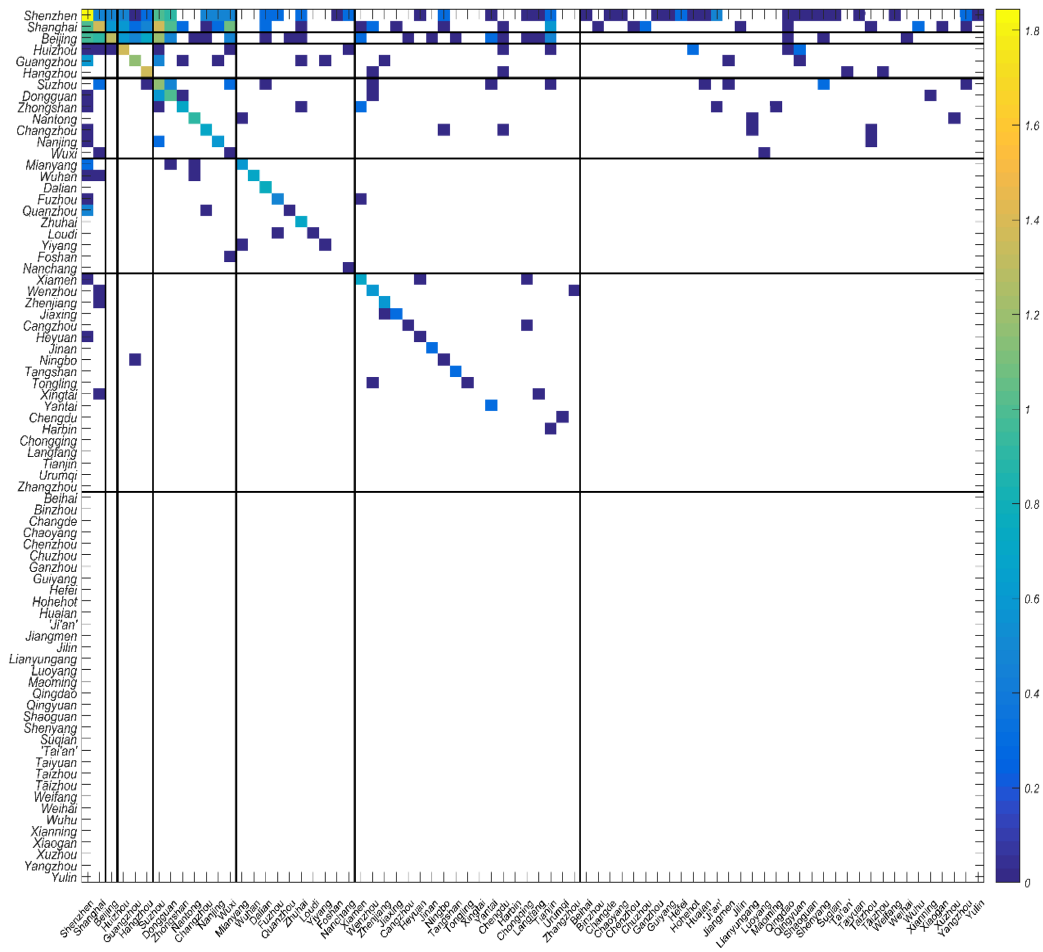


Figure 2.10: Heat map of city-based connectivity matrix (Colored by Log of edge weights) in city network formed by technology hardware and equipment firms

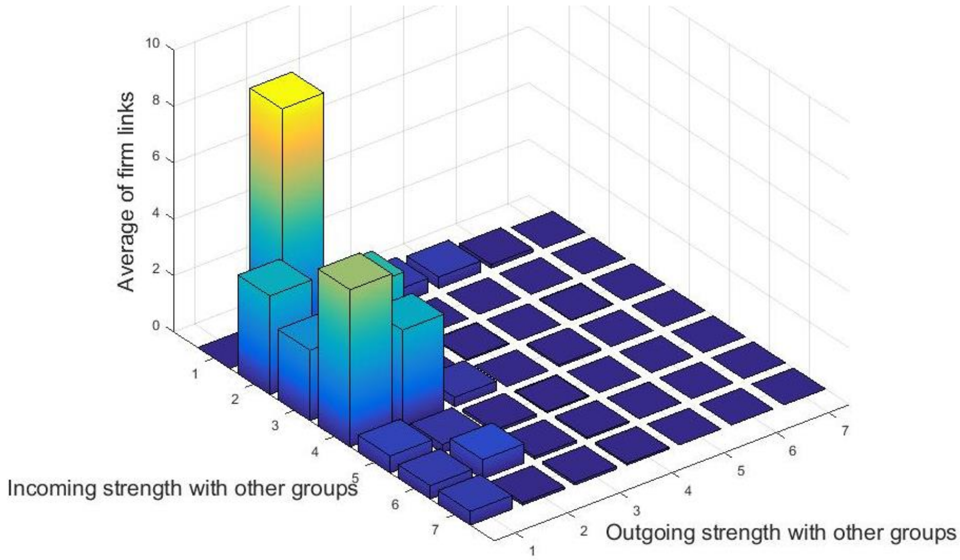


Figure 2.11: 3D block matrix of Meso-scale structure in city network formed by technology hardware and equipment firms

Meso-scale structures for the sector of technology hardware and equipment are investigated on a 76-city based connectivity matrix. The WSBM optimization identified 7 city blocks for which the corresponding heat map is given in Figure 2.10. It reveals a meso-scale structure that is a hybrid of the national CP structure and regional communities. Shenzhen and Shanghai in group one form the national core (α-Core) in the system; group 2 (Beijing) and group 3 (Huizhou, Guangzhou, and Hangzhou) are considered as β-Core as different level of connectivity with their peripheral cities (see Figure 2.15 for detailed partition results). Cities in group four, five and six are semi-peripheries that control a small number of subsidiaries in other groups. In contrast, cities in the last group (group 7) are peripheries with production plants and no outsourcing relations with other groups. Unlike the traditional Christallerian model that features a nested hierarchy of cities, we find that high-order functions locate in small and specialized cities (cities in groups 3-6) interconnected with cities from core groups. This result reinforces the organizational logic of complementarity network, which contains specialized and complementary cities interlinking together to achieve scale and agglomeration economies. Moreover, the intra-group links among cities are not only found in core groups but also in peripheral groups four, five and six, such as Suzhou and Dongguan. This provides evidence on the existence of a synergy network made up of big cities as well as smaller but specialized cities.

Given the features of the network associated with the pharmaceuticals and biotech sector, it is much harder to tease out the fundamental structures in contrast to the other two high-tech sectors. The heat map in Figure 2.12 suggests a single CP structure where the first group, made up of Shanghai, Beijing, and Chengdu, features as the core in the network. The remaining nine groups are peripheral, which altogether point to an overall structure that is widespread horizontally and vertically compressed. Cities in peripheral groups tend to connect with other spatially proximate cities. For example, parent companies in Xi'an (group 2) choose Baoji as the location of subsidiaries; Changchun (group 2) has a strong tie with the city of Tonghua in the same province; also, firms in Shijiazhuang (group 3) have attempted to establish their branches in the cities of Langfang and Baoding. Generally, the city network based on pharmaceutical and biotech firms lacks the distinctive meso-scale structure exhibited by the computing machinery and communications equipment sectors. These contrasting properties are strongly related to the stage in the industrial life cycle of these sectors. Study of the history of development of Chinese pharmaceutical firms indicates that most parent firms located in non-core cities and have existed in the market for decades. As the industry was easing a transition towards maturity in 2008, a core was in place, but a pattern of regional and fragmented communities of spatial proximity remained strongly in place across the production systems. Detailed partition results are given in Figure 2.16.

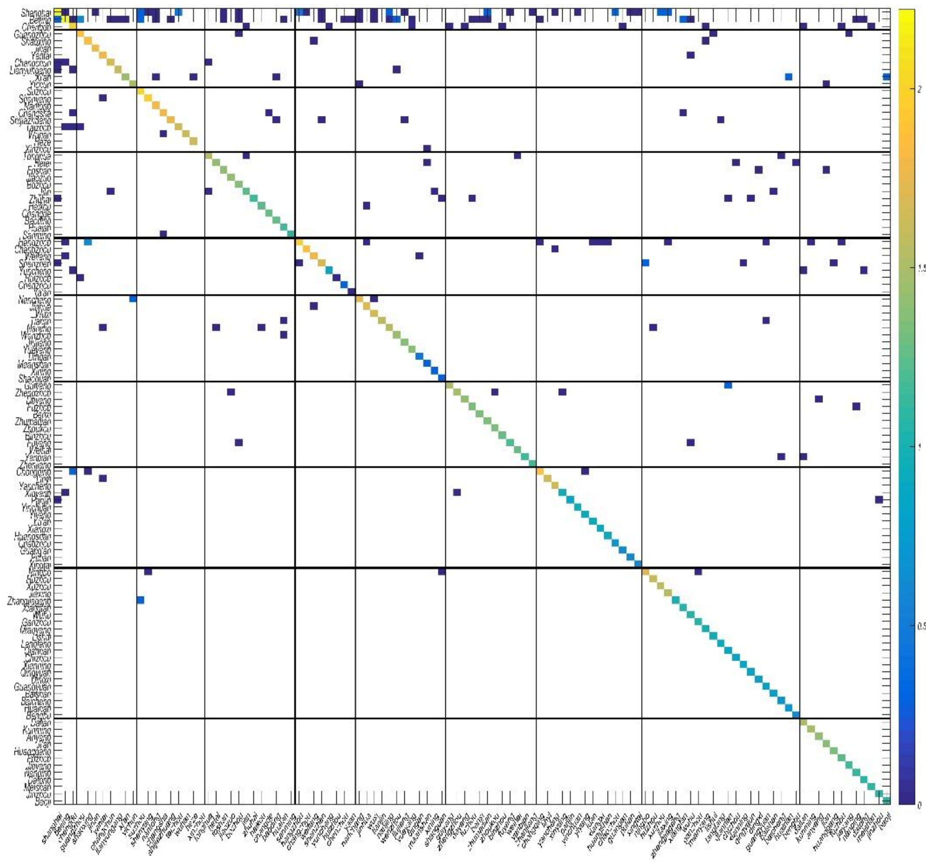


Figure 2.12: Heat map of the city-based connectivity matrix formed by pharmaceuticals and biotech firms (Colored by Log of edge weights)

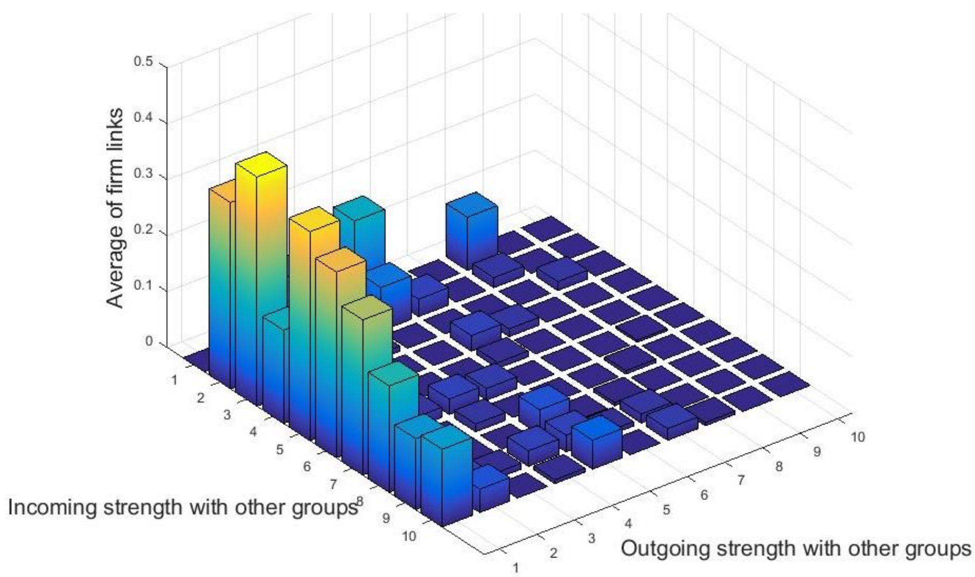
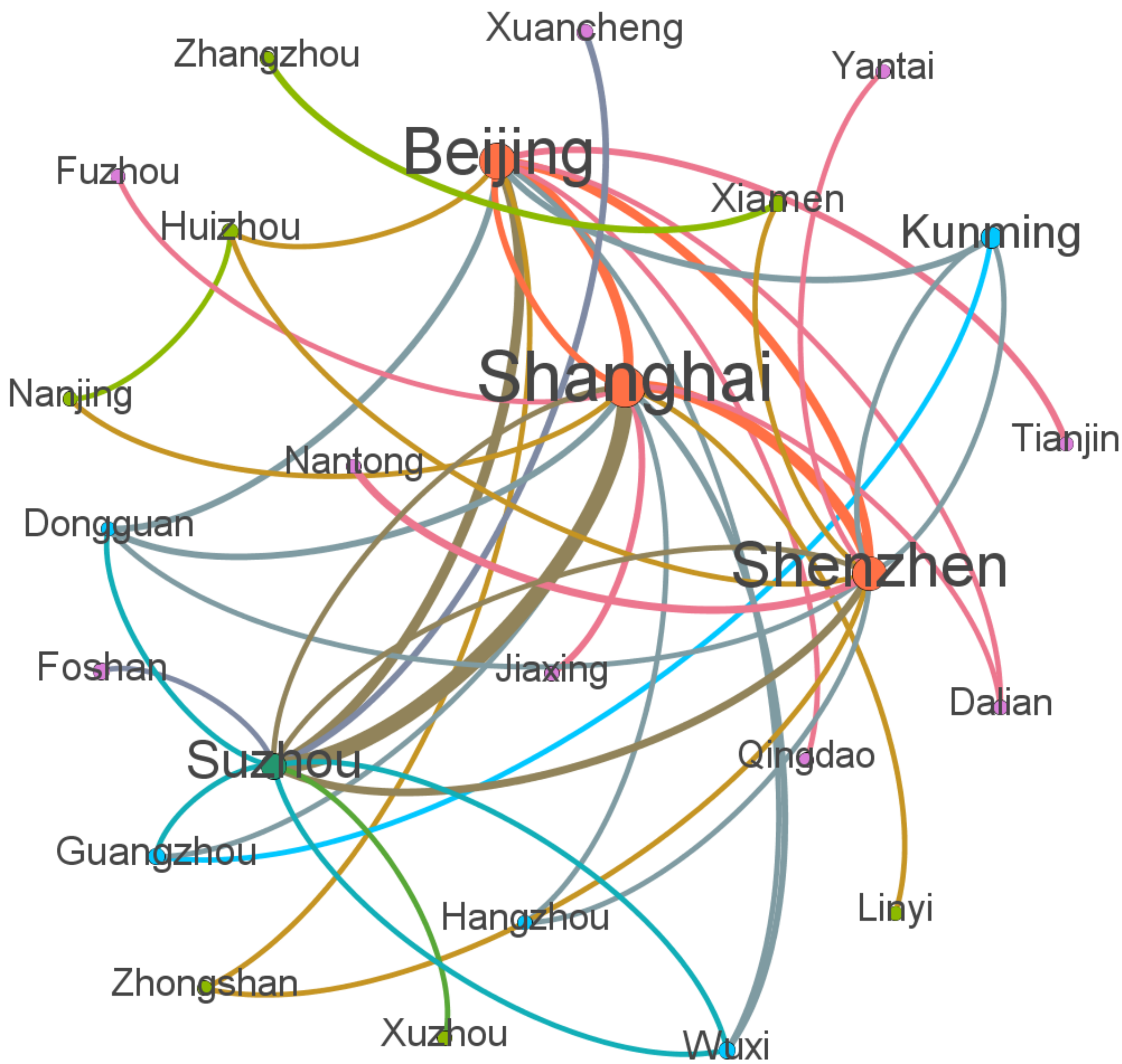


Figure 2.13: 3D block matrix of Meso-scale structure in city network formed by pharmaceuticals and biotech firms



Group (Number of Cities)	City name	Role
1 (3)	Shenzhen, Shanghai, Beijing	α-Core
2 (1)	Suzhou	β-Core
3 (5)	Dongguan, Guangzhou, Hangzhou, Wuxi, Kunming	Semi-periphery
4 (7)	Zhongshan, Xiamen, Nanjing, Huizhou, Zhangzhou, Linyi, Xuzhou	Periphery#1
5 (9)	Fuzhou, Foshan, Tianjin, Dalian, Jiaxing, Nantong, Yantai, Qingdao, Xuancheng	Periphery#2

Figure 2.14: Multicore-periphery structure in the city network and city distribution across groups based on office and computing machinery firms

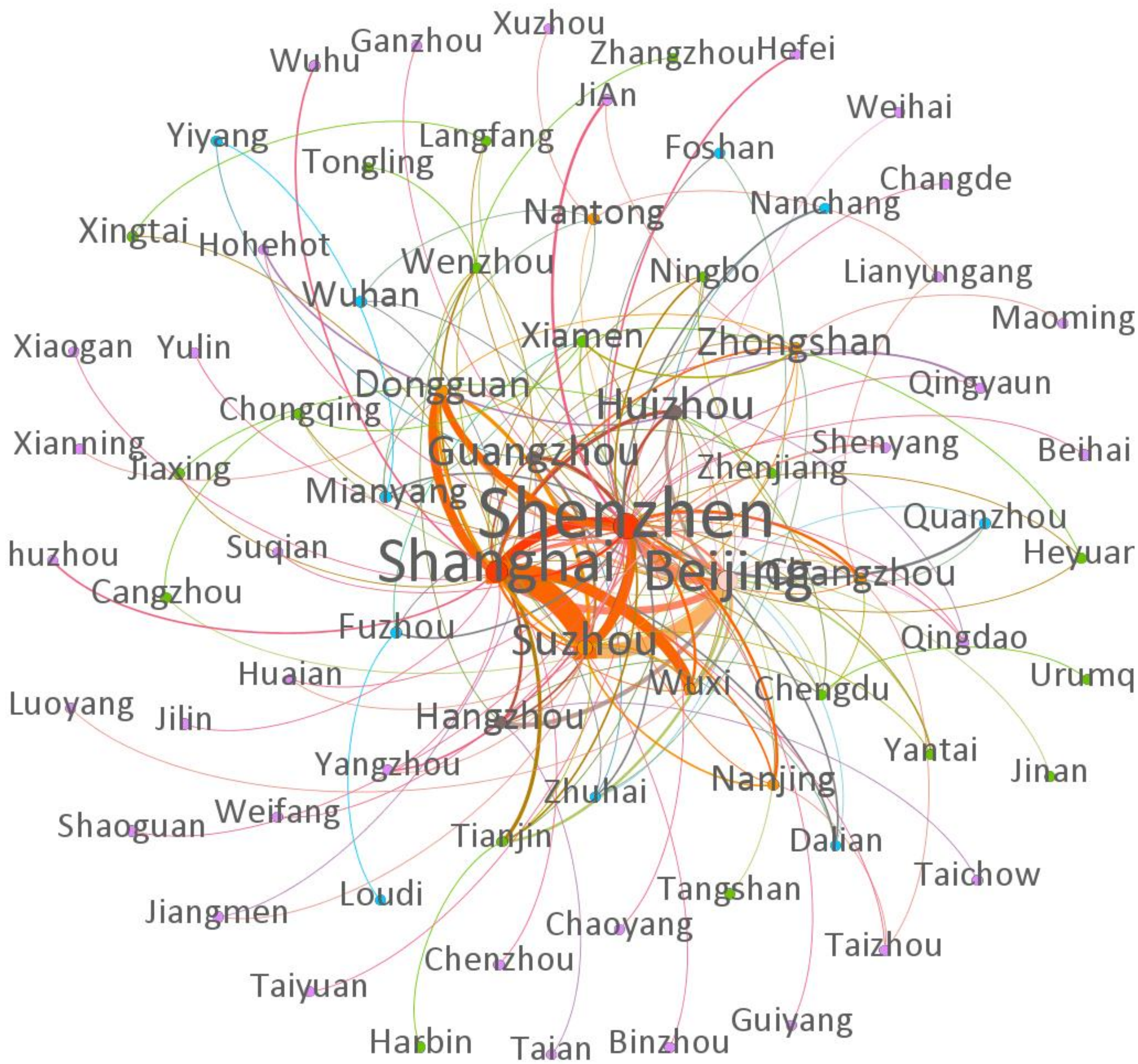


Figure 2.15: Multicore-periphery structure in the city network and city distribution across groups based on technology hardware and equipment firms

Group (Number of Cities)	City name	Roles
1 (2)	Shenzhen, Shanghai	α-Core
2 (1)	Beijing	β-Core
3 (3)	Huizhou, Guangzhou, Hangzhou	γ-Core
4 (7)	Suzhou, Dongguan, Zhongshan, Nantong, Changzhou, Nanjing, Wuxi	Semi-periphery#1
5 (10)	Mianyang, Wuhan, Dalian, Fuzhou, Quanzhou, Zhuhai, Loudi, Yiyang, Foshan, Nanchang	Semi-periphery#2
6 (19)	Xiamen, Wenzhou, Zhenjiang, Jiaxing, Cangzhou, Heyuan, Jinan, Ningbo, Tangshan, Tongling, Xingtai, Yantai, Chengdu, Harbin, Chongqing, Langfang, Tianjin, Urumqi, Zhangzhou	Semi-periphery#3
7 (34)	Beihai, Binzhou, Changde, Chaoyang, Chenzhou, Chuzhou, Ganzhou, Guiyang, Hefei, Hohehot, Huaian, JiAn, Jiangmen, Jilin, Lianyungang, Luoyang, Maoming, Qingdao, Qingyuan, Shaoguan, Shenyang, Suqian, Taian, Taiyuan, Taizhou, Taichow, Weifang, Weihai, Wuhu, Xianning, Xiaogan, Xuzhou, Yangzhou, Yulin	Periphery

Figure 2.15 continued

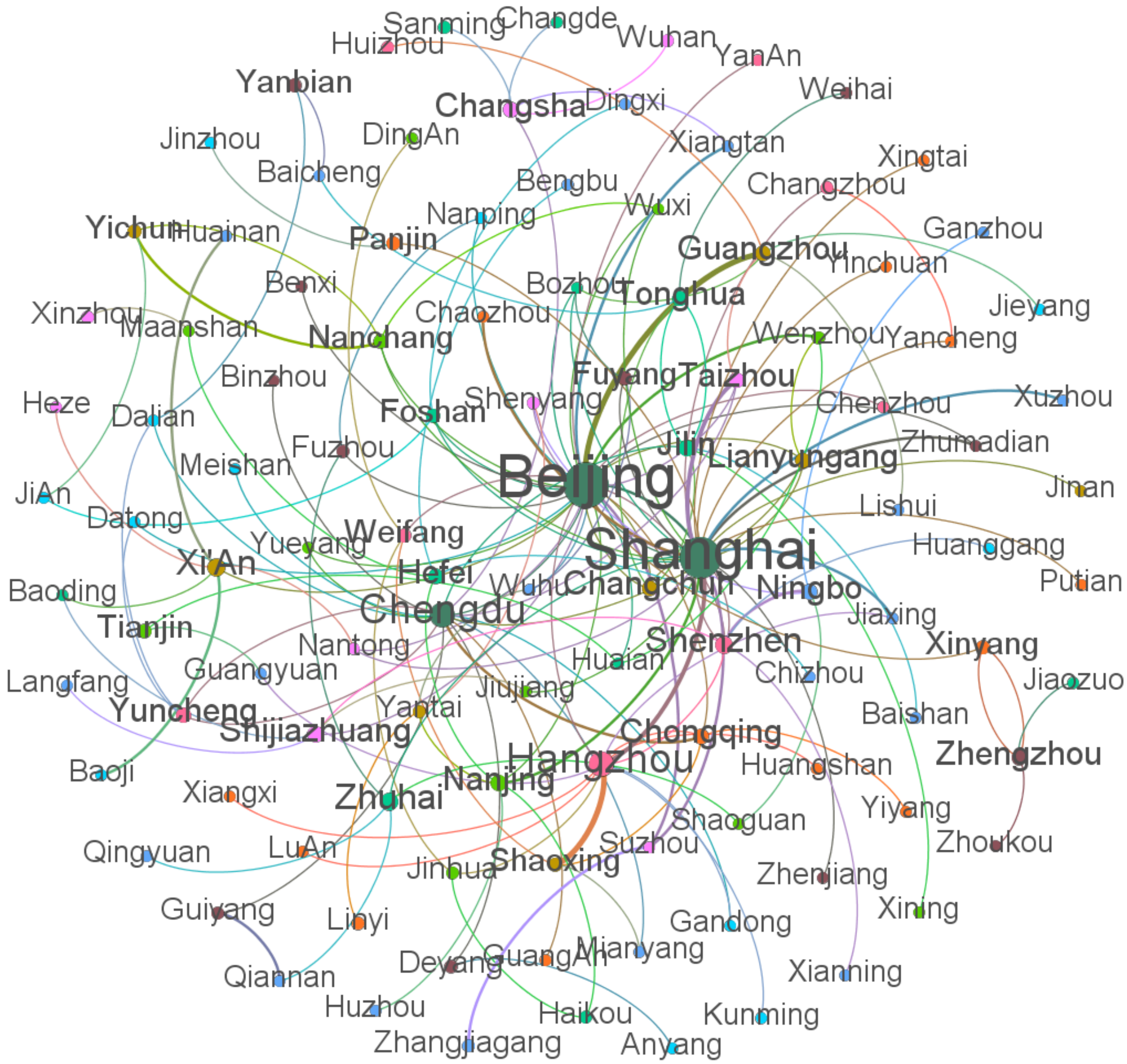


Figure 2.16: Multicore-periphery structure in the city network and city distribution across groups based on pharmaceuticals and biotech firms

Group (Number of Cities)	City name	Role
1 (3)	Beijing, Chengdu, Shanghai	α-Core
2 (8)	Changchun, Guangzhou, Jinan, Lianyungang, Shaoxing, Xi'An, Yantai, Yichun	Periphery#1
3 (9)	Changsha, Heze, Nantong, Shenyang, Shijiazhuang, Suzhou, Taizhou, Wuhan, Xinzhou	Periphery#2
4 (8)	Changzhou, Chenzhou, Hangzhou, Huizhou, Shenzhen, Weifang, YanAn, Yuncheng	Periphery#3
5 (12)	DingAn, Jinhua, Jiujiang, Maanshan, Nanchang, Nanjing, Shaoguan, Tianjin, Wenzhou, Wuxi, Xining, Yueyang	Periphery#4
6 (12)	Benxi, Binzhou, Deyang, Fuyang, Fuzhou, Guiyang, Weihai, Yanbian, Zhenzhou, Zhenjiang, Zhoukou, Zhumadian	Periphery#5
7 (12)	Baoding, Bozhou, Changde, Foshan, Haikou, Hefei, Huaian, Jiaozuo, Jilin, Sanming, Tonghua, Zhuhai	Periphery#6
8 (12)	Anyang, Baoji, Dalian, Datong, Gandong (Fuzhou), Huanggang, JiAn, Jieyang, Jinzhou, Kunming, Meishan, Nanping	Periphery#7
9 (14)	Chaozhou, Chongqing, GuangAn, Huangshan, Linyi, LuAn, Panjin, Putian, Xiangxi, Xingtai, Xinyang, Yancheng, Yinchuan, Yiyang	Periphery#8
10 (21)	Baicheng, Baishan, Bengbu, Chizhou, Dingxi, Ganzhou, Guangyuan, Huainan, Huzhou, Jiaxing, Langfang, Lishui, Mianyang, Ningbo, Qiannan, Qingyuan, Wuhu, Xiangtan, Xianning, Xuzhou, Zhangjiagang	Periphery#9

Figure 2.16 continued

2.6. Conclusions

The classical central place theory and its subsequent recastings along the lines of the New Economic Geography best describe the structure of the city system in strict economic and geographic terms, yet the theoretical assumptions display increasing dissonance with behaviors of economic activities in the actual space-economy. Under the conceptual framework of city network, the organization of the city-system underpinned by the constructs of complementarity network and synergy network could be abstracted as a new paradigm in urban and spatial economic sciences when precise conditions of exact meaning, theoretical economic rationale and empirical content are met. In this article, we used the complementary methods of network degree centrality and meso-scale network structure modeling to test the hypothesized network logics of a city system on the scale of mainland China through the headquarters-subsidiary relationships of firms. Our empirical analysis is implemented on 2008 firm-level data pertaining to each of three high-tech manufacturing sectors, and aggregated to prefectural cities of China. The city systems under study include several large cities (most notably Beijing, Shanghai and Shenzhen) together with other smaller cities that are mostly in the eastern part of China. No earlier empirical research has tested the network images framed by economic relations in the manufacturing landscape of China. Thus, this work contributes to the city network theory with empirical validation.

The concept of city network and its underpinnings are partly determined by the behavioral logic of firms when specialization and networking play important economic roles. A complementarity network allows cities to take advantage of the entire regional market in the specialized sectors and to achieve associated scale economies, so that a city can aspire to perform higher-order functions that once only happened in high-order cities in the urban system, as conceived by the traditional hierarchical model. By the same token, a synergy network emphasizes the need for innovative cooperation in order to reach critical mass by linking to cities with similar size and rank. As it has been argued, in some respects, the new theoretical underpinnings of complementarity and synergy networks may coexist in the context of certain specific industrial sectors.

In search of empirical validation of the city network theory, our research reached the following main conclusions. First, the high-tech city network exhibits macro- and meso-scale properties that align well with the organizational logics grounded in the theoretical economic rationale of firm behavior. We found evidence of both the complementarity network and the synergy network in China's high-tech manufacturing cities. On the one hand, cities with different functional specialization (headquarters versus subsidiary operations) and with division of labor partake in complementarity networks in all three industrial sectors; on the other hand, the shared goals and aspirations of cities that operate in the same functional tier provide impetus to their cooperation through the city network in order to reach economies of scale and emphasize the need for innovation. The synergy network is a notion that transcends any specific economic sector since it was found to be an important feature of how high-tech manufacturing cities organize within the national space-economy, while it was mainly considered in the financial and service cities in previous studies. Second, our results show that the city network reflected in high-tech manufacturing exhibits the properties ascribed to hybrid CP structure with regional communities. The national core is composed by three major cities (Shanghai, Shenzhen, and Beijing) inter-connected with a wide variety of specialized cities at a lower tier, while the semi-core comprises a few medium-sized cities with diverse industrial specialization. Lastly, the city network determined by the behavioral logic of the manufacturing firms shows different features in response to each of the three high-tech sectors. Some medium-size cities stand out by their high ranking of out-degree centrality. In this sense, medium-size cities in the Yangtze River Delta and Pearl River Delta regions present higher-order in computing machinery and technological equipment sector, whereas some cities from western and northeastern regions have disproportionately higher rankings for pharmaceuticals and biotech.

Through empirical validation on high-tech manufacturing activities, the paradigm of city networks brought into focus two important aspects of the city network. In future studies of the network-based urban hierarchies, we argue that there is a need for further scientific consideration of the dynamical evolution of the network and network externalities with longitudinal data series. Theoretical underpinnings could also be enhanced with data that convey the business functions performed by each establishment of a corporate entity that operates out of multiple sites, possibly in multiple cities. Finally, the study of various sectors, both at inter- and intra-city level, will provide more evidence on the city network paradigm.

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2.8. Appendix: City ranking

Table 2.5: City ranking in terms of out-degree and in-degree for respective sectors

A. Office and computing machinery

Ranking	City	Out-degree	Ranking	City	In-degree
1	Shanghai	30	1	Suzhou	23
2	Beijing	23	2	Shenzhen	12
3	Shenzhen	13	3	Shanghai	6
4	Suzhou	5	4	Dongguan	6
5	Kunming	4	5	Beijing	4
6	Xuancheng	2	6	Wuxi	4
7	Xiamen	2	7	Nantong	3
8	Foshan	1	8	Guangzhou	2
9	Guangzhou	1	9	Huizhou	2
10	Huizhou	1	10	Nanjing	2
11	Wuxi	1	11	Zhangzhou	2
12	Nanjing	0	12	Zhongshan	2
13	Zhangzhou	0	13	Dalian	2
14	Dongguan	0	14	Tianjin	2
15	Zhongshan	0	15	Jiaxing	2
16	Dalian	0	16	Hangzhou	2
17	Tianjin	0	17	Kunming	1
18	Qingdao	0	18	Xiamen	1
19	Linyi	0	19	Qingdao	1
20	Jiaxing	0	20	Linyi	1
21	Hangzhou	0	21	Fuzhou	1
22	Fuzhou	0	22	Yantai	1
23	Nantong	0	23	Xuzhou	1
24	Yantai	0	24	Foshan	0
25	Xuzhou	0	25	Xuancheng	0

B. Radio, TV and communications equipment						C. Pharmaceuticals and biotech					
Ran-king	City	Out-degree	Ran-king	City	In-degree	Ran-king	City	Out-degree	Ran-king	City	In-degree
1	Shanghai	98	1	Suzhou	61	1	Beijing	35	1	Chengdu	7
2	Shenzhen	78	2	Shenzhen	37	2	Shanghai	35	2	Shanghai	7
3	Beijing	72	3	Dongguan	25	3	Hangzhou	14	3	Beijing	6
4	Suzhou	17	4	Wuxi	22	4	Chengdu	11	4	Guangzhou	6
5	Guangzhou	14	5	Shanghai	19	5	Xian	7	5	Suzhou	6
6	Huizhou	13	6	Tianjin	12	6	Shenzhen	6	6	Shaoxing	5
7	Dongguan	8	7	Hangzhou	11	7	Zhuhai	5	7	Hangzhou	4
8	Zhongshan	7	8	Huizhou	11	8	Chongqing	4	8	Bozhou	4
9	Changzhou	5	9	Beijing	8	9	Jilin	4	9	Dalian	3
10	Hangzhou	4	10	Guangzhou	7	10	Nanjing	4	10	Nanchang	3
11	Mianyang	4	11	Changzhou	6	11	Shijiazhuang	4	11	Nanjing	3
12	Nanjing	4	12	Dalian	6	12	Changchun	3	12	Shenzhen	3
13	Quanzhou	4	13	Nanjing	6	13	Changsha	3	13	Taizhou	3

14	Nantong	3	14	Wenzhou	6	14	Guangzhou	3	14	Wenzhou	3
15	Wuhan	3	15	Xiamen	6	15	Hefei	3	15	Yantai	3
16	Xiamen	3	16	Zhuhai	6	16	Lianyungang	3	16	Nantong	3
17	Fuzhou	2	17	Chengdu	5	17	Nanchang	3	17	Wuxi	3
18	Wenzhou	2	18	Chongqing	4	18	Ningbo	3	18	Huaian	3
19	Wuxi	2	19	Jian	4	19	Taizhou	3	19	Xiangtan	3
20	Xingtai	2	20	Ningbo	4	20	Tonghua	3	20	Wuhu	3
21	Cangzhou	1	21	Qingdao	4	21	Yuncheng	3	21	Zhumadian	3
22	Chengdu	1	22	Qingyaun	4	22	Zhengzhou	3	22	Qiannan	3
23	Foshan	1	23	Shenyang	4	23	Yanbian	2	23	Jiaxing	3
24	Harbin	1	24	Yangzhou	4	24	Foshan	2	24	Changchun	2
25	Heyuan	1	25	Yantai	4	25	Fuyang	2	25	Changsha	2
26	Jiaxing	1	26	Zhongshan	4	26	Guiyang	2	26	Chongqing	2
27	Loudi	1	27	Fuzhou	3	27	Panjin	2	27	Foshan	2
28	Ningbo	1	28	Hohehot	3	28	Shaoxing	2	28	Fuzhou	2
29	Tongling	1	29	Langfang	3	29	Tianjin	2	29	Jilin	2
30	Yiyang	1	30	Nanchang	3	30	Weifang	2	30	Jinhua	2
31	Zhenjiang	1	31	Nantong	3	31	Xinyang	2	31	Ningbo	2
32	Beihai	0	32	Taizhou	3	32	Yichun	2	32	Shenyang	2
33	Binzhou	0	33	Chuzhou	2	33	Zhangjiagang	2	33	Tonghua	2
34	Changde	0	34	Hefei	2	34	Changzhou	1	34	Weifang	2
35	Chaoyang	0	35	Heyuan	2	35	Deyang	1	35	Yichun	2
36	Chenzhou	0	36	Huaian	2	36	Fuzhou	1	36	Nanping	2
37	Chongqing	0	37	Jiangmen	2	37	Haikou	1	37	Datong	2
38	Chuzhou	0	38	Lianyungang	2	38	Huizhou	1	38	Yueyang	2
39	Dalian	0	39	Mianyang	2	39	Jinhua	1	39	Yancheng	2
40	Ganzhou	0	40	Wuhu	2	40	Linyi	1	40	Fŭzhou	2
41	Guiyang	0	41	Zhenjiang	2	41	Sanming	1	41	Mianyang	2
42	Hefei	0	42	Beihai	1	42	Shenyang	1	42	Baicheng	2
43	Hohhot	0	43	Binzhou	1	43	Wenzhou	1	43	Jian	2
44	Huaian	0	44	Cangzhou	1	44	Wuhan	1	44	Guangyuan	2
45	Jian	0	45	Changde	1	45	Xinzhou	1	45	Maanshan	2
46	Jiangmen	0	46	Chaoyang	1	46	Yantai	1	46	Shaoguan	2
47	Jilin	0	47	Chenzhou	1	47	Dalian	0	47	Jiujiang	2
48	Jinan	0	48	Foshan	1	48	Jinan	0	48	Xuzhou	2
49	Langfang	0	49	Ganzhou	1	49	Bozhou	0	49	Chaozhou	2
50	Lianyungang	0	50	Guiyang	1	50	Nanping	0	50	Baoding	2
51	Luoyang	0	51	Jiaxing	1	51	Nantong	0	51	Baoji	2
52	Maoming	0	52	Jilin	1	52	Datong	0	52	Huainan	2
53	Nanchang	0	53	Jinan	1	53	Yueyang	0	53	Changzhou	1
54	Qingdao	0	54	Luoyang	1	54	Wuxi	0	54	Deyang	1
55	Qingyaun	0	55	Maoming	1	55	Benxi	0	55	Fuyang	1
56	Shaoguan	0	56	Quanzhou	1	56	Huaian	0	56	Guiyang	1
57	Shenyang	0	57	Shaoguan	1	57	Xiangtan	0	57	Haikou	1
58	Suqian	0	58	Suqian	1	58	Wuhu	0	58	Hefei	1
59	Taian	0	59	Taian	1	59	Suzhou	0	59	Jinan	1

60	Taiyuan	0	60	Taiyuan	1
61	Taizhou	0	61	Tāizhou	1
62	Tāizhou	0	62	Tangshan	1
63	Tangshan	0	63	Urumqi	1
64	Tianjin	0	64	Weifang	1
65	Urumqi	0	65	Weihai	1
66	Weifang	0	66	Xianning	1
67	Weihai	0	67	Xiaogan	1
68	Wuhu	0	68	Xuzhou	1
69	Xianning	0	69	Yiyang	1
70	Xiaogan	0	70	Yulin	1
71	Xuzhou	0	71	Zhangzhou	1
72	Yangzhou	0	72	Harbin	0
73	Yantai	0	73	Loudi	0
74	Yulin	0	74	Tongling	0
75	Zhangzhou	0	75	Wuhan	0
76	Zhuhai	0	76	Xingtai	0

60	Chenzhou	0	60	Lianyungang	1
61	Yaan	0	61	Shijiazhuang	1
62	Zhumadian	0	62	Xian	1
63	Changde	0	63	Xinyang	1
64	Yancheng	0	64	Yuncheng	1
65	Guangan	0	65	Zhengzhou	1
66	Fŭzhou	0	66	Benxi	1
67	Binzhou	0	67	Chenzhou	1
68	Meishan	0	68	Yaan	1
69	Mianyang	0	69	Changde	1
70	Yiyang	0	70	Guangan	1
71	Anyang	0	71	Binzhou	1
72	Baicheng	0	72	Meishan	1
73	Jian	0	73	Yiyang	1
74	Dingxi	0	74	Anyang	1
75	Lishui	0	75	Dingxi	1
76	Jieyang	0	76	Lishui	1
77	Qiannan	0	77	Jieyang	1
78	Luan	0	78	Luan	1
79	Jiaxing	0	79	Kunming	1
80	Guangyuan	0	80	Xiangxi	1
81	Kunming	0	81	Chizhou	1
82	Xiangxi	0	82	Bengbu	1
83	Chizhou	0	83	Baishan	1
84	Bengbu	0	84	Xining	1
85	Maanshan	0	85	Huangshan	1
86	Baishan	0	86	Huzhou	1
87	Xining	0	87	Ganzhou	1
88	Huangshan	0	88	Jinzhou	1
89	Huzhou	0	89	Putian	1
90	Ganzhou	0	90	Xingtai	1
91	Shaoguan	0	91	Yinchuan	1
92	Jinzhou	0	92	Zhenjiang	1
93	Jiujiang	0	93	Xianning	1
94	Xuzhou	0	94	Huanggang	1
95	Chaozhou	0	95	Langfang	1
96	Putian	0	96	Weihai	1
97	Xingtai	0	97	Dingan	1
98	Yinchuan	0	98	Heze	1
99	Zhenjiang	0	99	Zhoukou	1
100	Xianning	0	100	Jiaozuo	1
101	Huanggang	0	101	Qingyuan	1
102	Baoding	0	102	Yanbian	0
103	Langfang	0	103	Huizhou	0
104	Weihai	0	104	Linyi	0
105	Dingan	0	105	Panjin	0
106	Baoji	0	106	Sanming	0

107	Huainan	0	107	Tianjin	0
108	Heze	0	108	Wuhan	0
109	Zhoukou	0	109	Xinzhou	0
110	Jiaozuo	0	110	Zhangjiagang	0
111	Qingyaun	0	111	Zhuhai	0

CHAPTER 3 : CITIES IN INNOVATION

We seek to foster new ways of theorizing relational and network thinking across spatial scales and develop a conceptual framework that takes into account industrial clustering, organizational networking and technological relatedness to assess their impacts on knowledge creation by placing city at the heart of this process. Based on headquarters-subsidiary relationships in two sectors in China, we find that knowledge diffusion along the organizational network is significant but different for fast- (biotech) and slow-changing (technological equipment) knowledge-based industries. When tacit knowledge is paramount, it is more effective with spatially proximate collaborations; industries with codified knowledge are insensitive to physical distant.

3.1. Introduction

The integration of the network perspective with the geographic proximity framework is arguably one of the critical turning points in the study of innovation and economic growth (Balland, Boschma, and Frenken 2015; Glückler and Doreian 2016; Huggins and Thompson 2013). In line with knowledge-based theory, both the geographic clustering of businesses and the weaving of network ties between them are considered crucial for accelerating flows of knowledge and technology to spark effective innovation. In particular, organizational networks -a set of interdependencies cemented by business relationships among companies of a same organizational entity- enable interactive learning and benefit innovative activities. If both geographic proximity and social networking facilitate the transmission and sharing of knowledge, then one would expect knowledge diffusion to be particularly significant in cities as well as between cities owing to cities' high density and to the thick communication channels between them. Although progress has been made on theories closely articulating innovation and organizational relations, the extant research is still too scarce and fragmented to have established consensus theories of knowledge spillover and innovation (Glückler 2014; Ter Wal 2014; Zhu, He, and Zhou 2017). This article, therefore, aims to test theories of innovation in terms of spatial proximity and network relations using a new data set on Chinese cities and high-tech industries. We focus on statistically quantifying the respective roles of geographic proximity and organizational networks defined by the headquarters-subsidiaries relationships in fostering innovation in cities. Based on the activities of two sub-sectors of high-tech manufacturing between 2008 and 2011, we examine the understandings of various theories of knowledge spillovers and innovation on the influence of geographic concentration and organizational networking across 264 cities.

The concept of innovation is understood here in a narrow sense, as the creation of new ideas, new inventions or new business models to motivate technological advances. At the regional level, it features prominently in the theoretical elaborations of the Marshallian theory, singularly in connection with the process of knowledge spillover and how geographic proximity may facilitate it (Bathelt and Taylor 2002; Ellison and Glaeser 1997; Henderson 2010; Jaffe, Trajtenberg, and Henderson 1993; Porter 2000; Rosenthal and Strange 2004). However, this explains only part of the story when economic activities increasingly take the form of webs of interactions that may not necessary geographically proximity. In theories that position relationships and networking among firms as critically influential factors of the spatial organization of the economic system, network externalities provide the deciding impetus to actors in the form of economic benefits. Actors achieve scale economies and tap into greater opportunities by pursing innovation via networks of collaboration and cooperation that extend beyond geographical limitations (Bathelt, Malmberg, and Maskell 2004; Camagni and Capello 2004). Especially, the very existence of business relations between firm headquarters and their subsidiaries is largely overlooked in economic geography. Our contention is that a more refined theorization of these organizational networks and their impacts on innovation both across various spatial scales and between different agents (individuals, firms, cities and regions) is needed for various industrial activities.

In advancing our argument, we seek to place the city at the heart of the innovation process and then to investigate the modalities through which geographic proximity and organizational networks condition business innovation. Since regional scientists and geographers brought the spatial dimension into the theory of innovation, much has been written on the geography of innovation and on the micro elements that determine the geographical patterns of innovation. While it is now widely accepted that innovation is more likely to take place in cities or urban regions, an argument has been made that the city is indeed at the very heart of the innovation process. Specifically, it asserts that innovation is a social process that cannot be produced outside the context of cities and urban regions (Florida, Adler, and Mellander 2017). In a sense, it is not innovation in city but city in innovation. Cities are organically involved with innovative activities in generating new ideas and new organizational forms.

In this paper, we observe the current innovation system and recognize the coordination of economic activities based on the interactions between firm headquarters and their subsidiaries. In doing so, we bring together insights on the central role of cities in the processes of innovation from the organizational perspective. Our theoretical framework rests on a two-fold assumption, namely that the location choice of headquarters and subsidiaries is based on the economic rationale to maximize competitiveness, and that the organizational network of cities behind such behavior might play a role in knowledge spillovers beyond pure geographic concentration. Thus, in our empirical scenario, the knowledge production function (KPF) framework relates innovation inputs to new product output to validate various theories of knowledge spillover and innovation based on data on Chinese non-listed private high-tech manufacturing firms in the period of 2008-2011. Since the data span a short period, we rely on the spatial Durbin model (LeSage and Pace 2009) to study the marginal and joint effects of local clusters and organizational network on innovation. For this purpose, we adopt a novel spatial approach (Hazir, LeSage, and Autant-Bernard 2016) to take into account the co-existence of local clusters and organizational city network across spatial scales. The best model fit is determined by the optimization of the log-likelihood with respect to the combination of three components of the weight matrix (local, proximate, and distant). Our research questions are as follows. First, does the organizational city network contribute to knowledge spillovers across territories? Second, based on the different types of city interactions (local, proximate, and distant), what types of knowledge spillovers occur between cities, and what is their impact on cities' absorptive and learning capacity in the city network context? Third, do differences exist in the network effects and types of knowledge spillovers across various industrial activities? The rest of the paper is structured as follows. First, a literature review on industrial linkages and knowledge creation is conducted. Next, the model and data description are introduced. Empirical results are presented in section four, followed by our conclusions.

3.2. Theoretical background

Starting with the new growth theory (Romer 1986), economic externalities stemming from knowledge and technology spillovers have featured prominently as catalyst of innovation and city growth. Several specific theories center on technological spillovers, whereby innovative improvements in one firm may increase the productivity of the other firms without paying compensation (Glaeser et al. 1992). First, the Marshall-Arrow-Romer (MAR) externality and Porter's industrial clusters focus on the spillovers between firms in the same industry in close geographic proximity. The geographic concentration of firms is a powerful conduit, which not only facilitates the movement of material and information but also facilitate the exchange of ideas, knowledge and social interaction (Camagni et al. 2013; Rosenthal & Strange 2004). In this sense, interactions among firms from the cluster and co-located geography deeply impact on firms' creation of new technologies and products. The difference between MAR externalities and Porter's model boils down to local competition. While MAR externalities address the local concentration based on internalized externalities (such as a monopoly), Porter supports local competition to increase the innovative pressure of firms.

The second theory proposed on knowledge spillovers is that of Jacobs' externalities (1969). Unlike the externalities from firms in the same industry, Jacobs' idea emphasizes the spillovers from the diversity of activities located in large cities, which in turn gives rise to higher innovation in various industries. In other words, industrial variety in Jacobs' theory is crucial in transferring knowledge and improving innovation, rather than industrial specialization (Glaeser et al. 1992). From an empirical perspective, a large body of literature is dedicated to distinguishing the impacts of MAR and Jacobs' externalities on growth and innovation then draw comparisons between places that differ by the source of externalities. In other words, early theories of externalities assume that knowledge spillovers attenuate with distance. Thus, firms in same industry should be geographically close to each other in order to absorb the knowledge and each firm is assumed to have equal a priori opportunity to receive various spillovers (Rosenthal and Strange 2001).

Later, with the various range of the geographic scope of a cluster and the broad characterization, it was argued that knowledge spillovers are in fact uneven and that interactions are selective among firms in the industrial (Bathelt et al. 2004; Bathelt and Taylor 2002). More significantly, firms' behaviors became more complex through various business forms of collaboration and cooperation, which allow them to break the local boundaries and move toward a wider range of spatial forms. All these started to raise doubt on whether geographic proximity still plays a controlling role in knowledge spillovers and whether other forms of network interactions may better explain innovation (Balland et al. 2015; Boschma 2005). It is in this context that an organizational network can be proposed as a construct of non-geographic proximity to explain the mechanism of interactive learning and its effect on innovation. An organizational network describes the membership of firms to the same organizational entity, for example, subsidiaries of the same parent company in high-tech manufacturing industry. In principle, because the exchange of knowledge requires strong ties to overcome uncertainty, an organizational network is believed to enrich the probability of learning and creation, especially in high-tech firms. It can reduce the risk with regard to ownership rights and ensure adequate profits from their own investments in new technology (Boschma 2005).

While traditional theories identified the significance of geographic clustering and localization of industrial activity in the innovative economy, the network concept and evolution in economic geography has brought deeper insights into the field of knowledge spillover and innovation. The fundamental challenges brought by organizational networks to traditional understandings have two dimensions. First, organizational networks, especially in the high-tech manufacturing industry, refine the concept of technological relatedness and enhance the conceptualization in the space economy. Relational analysis is central to study the relatedness of technologies and their roles in fostering regional growth and innovation (Boschma et al. 2012; Glückler and Doreian 2016). Technological relatedness is anticipated to effect knowledge spillovers both in short and long terms. It is argued that technological relatedness could transfer learning opportunities and to create more knowledge spillover to drive growth of surviving industries in the short term; it also plays a key role in opening new pathways for new industries in the long term. However, these results are mainly obtained at the macro level with a coarse characterization of technological relatedness (Boschma et al. 2012; Boschma and Capone 2016; Coe 2011; Essletzbichler 2015), such as using export data (Zhu et al. 2017). Thus, we know little about the mechanism of knowledge spillover in terms of various technological relatedness embedded in the micro organizational relations, such as headquarters and subsidiaries in high-tech manufacturing.

Second, it is assumed that the organizational network makes a difference in knowledge spillover and learning among different entities. By the same token, while firms in the same organization may be located in different places, organizational networks may be leveraged to overcome spatial limitations and help to transmit knowledge among different firms at various spatial scales through its organizational ties. Hence, the network evolution allows knowledge spillovers to occur not only within local clusters but also beyond the local territory, according to theoretical foundations. As such, one would expect the structure and evolution of network ties to mediate the transfer of knowledge between different organizational nodes in the space. For example, there are studies with data on patent coauthorship (Cassi and Plunket 2014; Strumsky and Thill 2013) and investment activities between two countries (Bathelt and Li 2014; Glückler 2014). However, the prevalent structure of headquarters and their subsidiaries in high-tech industries has so far been overlooked. In this context, in order to address the research gap on the trade-off between the advantages of spatial clusters and the richness of distributed headquarters and subsidiaries, our conceptual framework builds upon the economies of externality and organizational network in knowledge transmission. By so doing, we emphasize the interplay between local clusters embedded in a network configuration and investigate the types and extent of knowledge spillovers through organizational ties across cities.

3.3. Research design

3.3.1. Model and an alternative weight matrix approach

Our empirical investigation relies on a spatially extended Griliches-Jaffe knowledge production function (KPF) framework aggregated at the city level to evaluate innovation input and output in a single industry. Here, the focus is on the role of knowledge spillovers arising from the local territory or from cities being involved in an organizational network through which knowledge diffuses over time (Sheng and LeSage 2016). A standard feature of KPF is to assume an augmented production function with value-added innovation output in city i (Inn_i) expressed as a function of local standard inputs (industrial externalities) ($Characteristics_i$), internal research input specific to the industry ($InternalInput_i$), and public expenditure in research ($ExternalInput_i$). The Cobb-Douglas function is adopted for estimation and a baseline description shows as follows:

$$Inn_i = \alpha(Characteristics_i)^{\beta_1}(InternalInput_i)^{\beta_2}(ExternalInput_i)^{\beta_3} \,. \qquad (3.1)$$

From a theoretical perspective, it is rational to assume that some inputs to the innovative production process formulated by (3.1) cannot be observed (Autant-Bernard and LeSage 2011). Hence, a Spatial Durbin Model (SDM) specification is considered to handle the observable and unobservable inputs in the spatial regression extension to KPF. After taking the log-linear form, equation (3.1) can be expressed as:

$$y_t = \lambda W y_t + X_{t-k}\beta + W X_{t-k}\delta + c + \alpha_t l + v_t \,, \qquad (3.2)$$

where y_t is a column (logged) vector of innovation output on *n* regions at a particular time *t* and for a specific industry, W is an $n*n$ weight matrix with three spatial components as defined in Eq. (3.3). λ is the parameter exhibiting the strength of dependence among cities' innovation outputs, X_{t-k} is a matrix of locally and time-varying non-stochastic variables of regional inputs to innovation, k is the time lag of effects on outputs, β represents a vector of coefficients for innovation inputs, δ is the parameter indicating the strength of dependence among regions' innovation inputs, *c* is a column vector of individual effects, α_t is the t^{th} element of the m*1 column vector of fixed time effects, l is an n*1 constant term vector associated parameter α to accommodate situations when y does not have a mean value of zero, v_t is an n*1 column vector of identically and independently distributed error terms with standardized normal distribution. In this model, k = *{1, 2, 3}*, one to three years of time lag are assumed to allow for the generation of new product as a result of certain input conditions. Although the time lag of the dependent variable is applied, this model is still static with regard to the time lags of the dependent variable. This specification allows us to examine the impacts of intra-temporal knowledge ties among cities by quantifying the static effects of knowledge.

In order to specify the weight matrix, we adopt an alternative approach proposed by Hazir et al. (2016). In this method, there are n regions (cities) and W_{n*n} is the weight matrix demonstrating the interaction structure that controls the regional knowledge spillover processes. W is further decomposed as a convex combination of three mutually exclusive components: W_1, W_2, W_3, where W_1 is the matrix of spatially proximate cities that do not have organizational relations; W_2 shows the strength of organizational interactions among spatially proximate cities; and W_3 indicates the strength of organizational links among distant city pairs. A more detailed explanation on the construction of matrices is given in section 3.3.3. W_1, W_2, W_3 are all rownormalized so that W has row sums of one. λ_1, λ_2, λ_3 are the corresponding scalar weights for W_1, W_2, W_3, respectively, so W can be expressed as:

$$W = \lambda_1 * W_1 + \lambda_2 * W_2 + \lambda_3 * W_3 \tag{3.3}$$

$$\lambda_1 + \lambda_2 + \lambda_3 = 1$$

The identification of the W matrix starts with the case where $\lambda_1 = 1$, and$\lambda_2 = \lambda_3 = 0$, where dependence of output on regional knowledge spillover is assumed to be driven purely by local agglomeration. Later, with a step size of 0.1, we increment λ_2 and λ_3 using a looping procedure to calculate the log-likelihood for each of 66 possible combinations. At last, the model fit is compared with the changes in the corresponding scalar weights via the log-likelihood value (Hazir et al. 2016).

Compared to the traditional method of spatial weight matrix, this approach provides several advantages in analyzing the effect of network behavior. First, it allows us to assess the relative strength of different dependence structures, which dovetails well with our research objectives. The matrix W_1 and the scalar parameter λ_1 provide an overall assessment of the significance of various mechanisms accounting for local knowledge flows. The matrices W_2 and W_3 with associated parameters λ_2 and λ_3 help to distinguish the role played by proximate and distant partners in organizational network. Second, this approach also allows us to tease out and interpret direct and indirect effects based on conventional matrix derivatives for partials and cross-partials. Third, while this methodology was originally introduced on patent data to examine collaboration networks and regional knowledge creation, it can also be applied to explore other channels. Hence, this method provides us with an important and novel tool to extend the understanding of spatial diffusion of knowledge from the local scale to a scale that spans across cities (Hazir et al. 2016)

3.3.2. The sample and the data set

As an empirical analysis, model (3.3) is implemented to quantify the effect of organizational network on the innovation-driven activity of Chinese cities in two high-tech sectors. According to the ownership modalities, firms (either listed or non-listed) can be differentiated into state-owned enterprises (SOEs), foreign-owned enterprises (FOEs), and privately-owned enterprises (POEs) (Zhu et al. 2019). Given our research purpose, POEs and FOEs are considered hereafter but SOEs are excluded from the analysis according to the assumption that firm behavior is determined by market. We primarily draw from three data sources to prepare a data set on prefectural cities with high-tech firms within the 2008-2011 period, namely *China Non-listed Enterprise Database*, *China Industry Statistical Yearbook*, and *China City Statistical Yearbook.*

There is consensus that different manufacturing sectors support knowledge flows via diverse mechanisms (labor mobility, trade, research collaborations, for instance) to some degree. As a result, the spatial roles played by geographic proximity and organizational proximity in network externality may also be quite varied. In this research, we specifically focus on two high-tech sectors: pharmaceutical and biotechnology, and technology hardware and equipment industry, according to the 4-digit industry coding. This choice is motivated by two primary considerations. First, although these two sectors are knowledge-intense manufacturing, they stand at different stages of their life cycle, with high-tech equipment being a sector at an advantage stage of development and moving fast towards maturity, whereas the biotech sector is still accelerating its development with highly intensive knowledge (Krätke 2014). With these two sectors, we can represent a range of conditions and capture the differences in the knowledge flows in accordance with innovation and production activities. Second, the number of link and node entities in the organizational networks of other high-tech sectors (such as computer manufacturing) can be quite limited, which reduces the range of configurations that can possibly be featured, while the selected sectors have a more complete city network that spans across the country.

In building the organizational city networks, we first sort out the firms that belong to each of the industry sub-sectors of technology hardware and equipment, and pharmaceuticals and biotech. Second, the organizational city network of each industry is built from the corporate headquarters and subsidiaries mapped onto their corresponding city locations. For domestic POEs, we directly assemble corporate affiliations to detect each firm's hierarchy – such as headquarters, divisions, subsidiaries, affiliates, and joint ventures – and tie to city geography. The case of FOEs is handled a little differently. Here, we use the position of regional corporate centers holding the highest level of corporate functions in China; also, FOEs include enterprises from Hong Kong, Taiwan, and Macao, as recognized by the National Bureau of Statistics. After identifying the connections between subsidiaries and their headquarters, the geographies of these firms are aggregated into the city level for the sake of network analysis shaped by the different industrial sectors.

Overall, as shown in Table 3.1, 264 of the 337 prefectural cities house facilities of either of the two industrial sectors in our study. Since our empirical scenario is static, the organizational networks of headquarters and subsidiaries are constructed for the single year of 2008. In 2008, there were 9,548 private firms in technology hardware and equipment, 631 of them being subsidiaries or plants located in cities different from the location of their headquarters. 4,548 firms were in the sector of pharmaceuticals and biotech, among which 539 subsidiaries were located in cities other than their headquarters. When firm data are integrated to cities, 76 cities are in the organizational network of the technology hardware and equipment sector, and 111 cities compose the pharmaceutical/biotech network.

Table 3.1: Summary of two sectors in the study

	Total firms	Total cities	Total subsidiaries	Subsidiaries located in different cities from HQ	Network cities with organizational links
Pharmaceuticals and biotech	4,548	264	539	293	111
Technology hardware and equipment	9,548	264	631	356	76

There are several possible indicators of innovation, including patent applications, granted patents, or new product output (Sheng and LeSage 2016). Given the measurement limitation of patents that may not truly reflect the innovative activities in the industry, in this research, the dependent variable of city technological innovation is represented by the value of new product output in each year from 2009 to 2011. To draw a contrast in the space-time analysis of different knowledge flow externalities on innovation, we also estimate a benchmark model of overall city production where total product output is the dependent variable. As explained earlier, we use different time windows for the dependent variable and the independent variables due to the fact that knowledge creation and innovation take time. Considering data availability, we assume a lag of three years. Thus, the time range for the dependent variable is 2009-2011, while 2008 is used as a base for the explanatory variables as well as for the construction of organizational networks.

Drawing on the regional innovation literature, we specify the model with four groups of knowledge input of cities as explanatory variables. The first measures the three key sources of externalities for city innovation, namely urbanization, diversity and specialization. We use the location quotient (LOC) of employment at the 4-digit manufacturing sector level to measure the industrial specialization of a city region. Urbanization, also known as Jacobs' externalities, captures the diversified level of human activities and urban amenities, which may have either a negative or positive impact on production and innovation activities. It is measured by the private-sector employment in each city. Finally, as a concept that contrasts with specialization, diversity captures the differences in regional industrial diversity and is calculated by the share of employment in non-top-5 sectors of 4-digit industries (Renski 2011). The second group of explanatory variables pertains to financial inputs, including regional science expenditure and internal R&D input of each sector. Regional science expenditure is the public spending on all types of research activities, whereas internal industry R&D input is aggregated by firm-level R&D input to approximately capture the regional R&D input in specific high-tech sectors.

The third and fourth variables are considered to capture the influence of human resources and export, respectively. We use the number of faculty members per university weighted by the number of universities rated '211 Project' to indicate the human capital available. The designation '211 Project' encompasses flagship provincial universities for the purpose of priority to receive public financial support grow faster than other universities. It has been argued that export orientation may increase innovation to meet the higher standards in global markets (Sheng and LeSage 2016). With China being the largest export country in the world, we also consider the regional export value of each high-tech sector by aggregating the firm-level export value. All the variables are log-transformed based on the KPF function, so the coefficients estimate the elasticity responses of innovation output to changes in independent variables.

3.3.3. Construction of spatial weight matrices

To disentangle the effects of geographic proximity and social networking, the spatial weight matrices (W) are built upon the three matrices W_1, W_2, W_3 mentioned earlier, for each sector. For this purpose, we first define contiguous cities using the rook criterion that a common edge exists between spatial entities representing them. For W_1, $W_{1_{ij}} = 1$ if and, only if, cities i and j are geographically proximate (i.e., share a common border) and have no corporate relationships between headquarters and subsidiary firms. For W_2, $W_{2_{ij}} = 1$ if cities i and j not only share a common border but also have some organizational relationship. Finally, we define $W_{3_{ij}} = 1$ for city pairs that do not share any physical borders but are organizationally connected with each other. All three matrices are row-standardized.

It should be pointed out that the conditions on the three matrices are intended to be mutually exclusive. Also, although W_1 is designed to account for spillover among city neighbors that lack any organizational network relations, it may also encompass some other latent social networking effects, such as social and institutional interactions (Balland et al. 2015). Finally, in line with a number of empirical studies (Balland et al. 2019; Bathelt et al. 2004; Jaffe, Trajtenberg, and Henderson 1993; Rosenthal and Strange 2003; Zhang and Wu 2019), we take the position that W_1 also comprises spillover effects that are entirely within the confines of the city boundaries, including both intentional (such as organizational interactions in the city) and unintentional effects (pure spillovers). When they are internal to the city, these effects covary with the spillover effects measured outside the city, so that the latter serve as proxy of the former and the mechanism of place-based relatedness is implicitly embedded in the W_1 weight matrix. Figures 1 and 2 illustrate the spatial structure of the organizational networks for the two high-tech sectors.

When estimating the spatial regression model, simultaneous feedback could arise from dependence relations (LeSage and Pace 2009). As in the case of SDM, model (3.2) can be further expressed as:

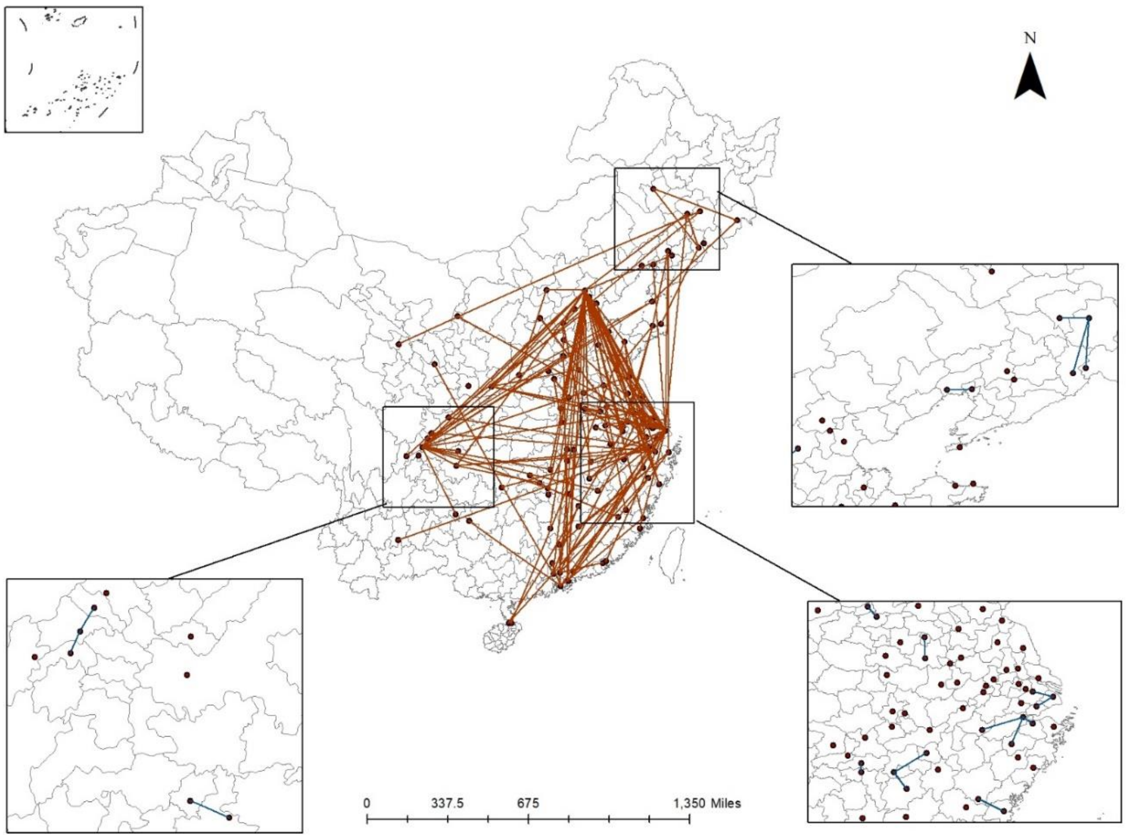
$$y_t(I_n - \lambda W_{y_t}) = X_{t-k}\beta + WX_{t-k}\delta + c + \alpha_t l + v_t \; , \tag{3.4}$$

$$y_t = \left(I_n - \lambda W_{y_t}\right)^{-1} X_{t-k}\beta + \left(I_n - \lambda W_{y_t}\right)^{-1} WX_{t-k}\delta + \left(I_n - \lambda W_{y_t}\right)^{-1}\varepsilon \tag{3.5}$$

The inverse $(I_n - \lambda W)^{-1}$ can be expressed as an infinite sequence: $I_n + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \cdots$,

$$y_t = X_{t-k}\beta + \lambda W_{y_t} X_{t-k}\beta + \lambda^2 W_{y_t}^2 X_{t-k}\beta + \cdots$$
$$+ W X_{t-k}\delta + \lambda W_{y_t} W X_{t-k}\delta + \lambda^2 W_{y_t}^2 W X_{t-k}\delta + \cdots$$
$$+\varepsilon + \lambda W_{y_t}\varepsilon + \lambda^2 W_{y_t}^2 \varepsilon \tag{3.6}$$

The rows of weight matrix W are constructed to represent first-order contiguous neighbors. The matrix W^2 thus reflects *second-order* contiguous neighbors, those that are neighbors to the first-order neighbors. In W^2, second-order neighbors also include observation *i* itself; thus the weight matrix has positive elements on the principal diagonal. As a result, high-order spatial lags can lead to a connectivity relation for an observation *i*, which produces a small feedback effect where a change in the value of neighboring region *j* will feedback to region *i*. In line with the static cross-sectional model, the observations reflect a steady equilibrium outcome, as a result feedback effects are considered instantaneous and their interpretation should indicate a movement to the next steady state (Anselin 2013; LeSage and Pace 2009).



Spatially proximate organizational network (W_2)

Long-distant organizational network (W_3)

Figure 3.1: Organizational city network of pharmaceuticals and biotech

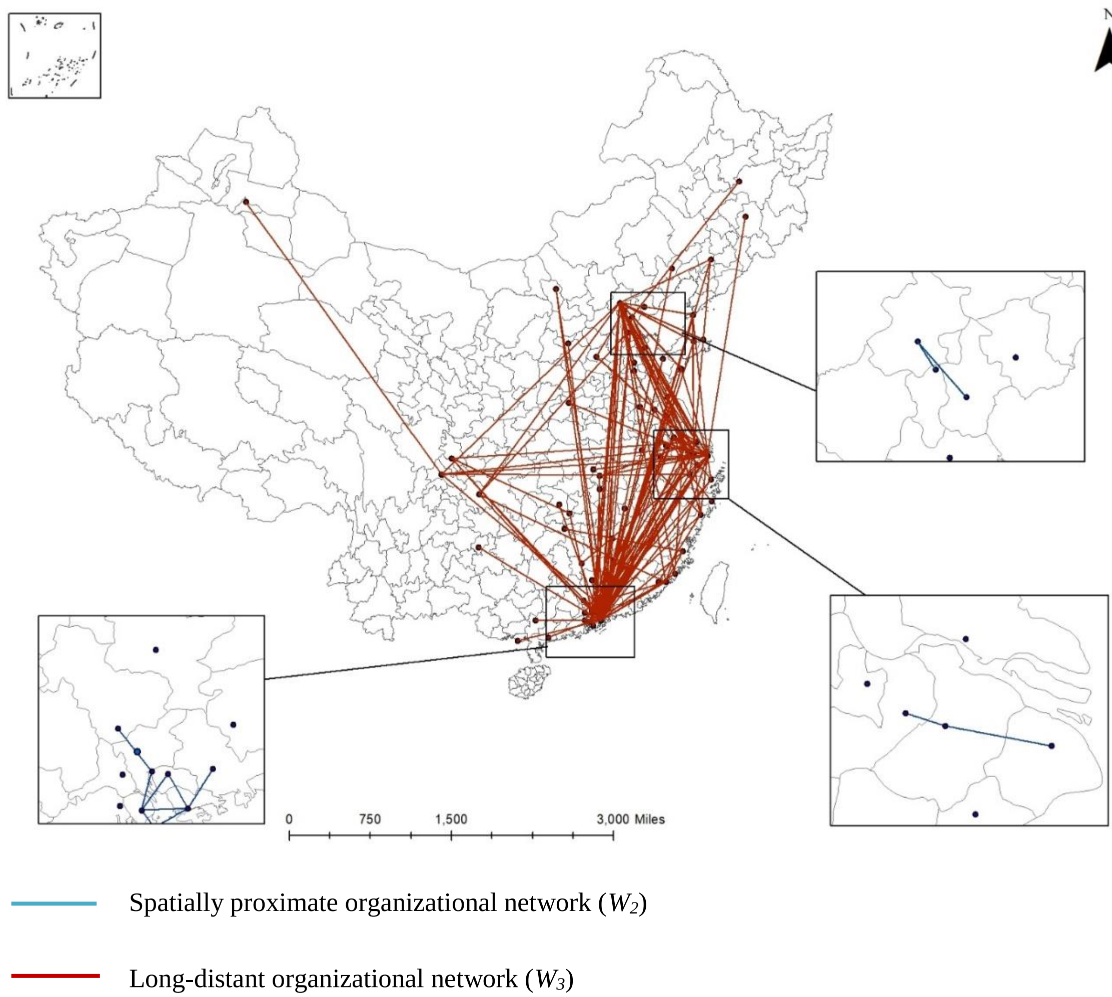


Figure 3.2: Organizational city network of technology hardware and equipment

3.4. Results

3.4.1. Spatial and network effects in regional pharmaceutical and biotechnology industry

Estimation results on innovation in the pharmaceutical and biotech industry as measured by the value of new products from 2009 to 2011 are presented in Table 3.2 and Tables 3.4-3.7. We start with the analysis of relative weights of components of the spatial matrix *W*, to study the respective roles of spatial effects and network effects. Table 3.2 reports the combinations of weights ($\lambda_1, \lambda_2, \lambda_3$) on spatial matrix *W* that have the ten highest likelihood values. The case of new product output can be evaluated against the case of gross output (Table 3.3) to tease out the specific behaviors when innovation drives the economic activities.

Several important results can be drawn from Tables 3.2 and 3.3. First, the best model fit for new product output is obtained when a relatively larger weight (at least 20% in Table 3.2) is assigned to spatially proximate city organizational interactions (W_2) and to distant partners (W_3), especially in the first two years after 2008; the balance of 50-60% is assigned to local externalities (W_1). In contrast, for gross production, 90% of the weight is assigned to local externalities (W_1) and only a small weight (10%) to spatially proximate city interactions (W_2), as shown in Table 3.3. Second, the increasing weight of W_2 and the decrease in W_3 weight over time underscore the role played by a geographically organizational interactions (via W_2) in regional knowledge creation in the biotech industry. In addition to the growing importance of spatially proximate collaboration, other types of proximate interactions also have a great impact on spatially proximate knowledge spillovers including non-organizational, face-to-face connections. As a result, reviewing the combination results of three weights for the production output of the biotech industry in each city, we have evidence that knowledge spillovers are overwhelmingly derived from spatial concentration where the tradition agglomeration economies are effective. However, the magnitude of the weights W_2 and W_1 implies that network externalities reflected by local interactions and interactions with proximate cities have great and growing impacts on knowledge creation and business success in the pharmaceutical and biotech industry. For gross production (Table 3.3), we find no meaningful changes in weights over time and local proximity-induced effects dwarf any others. Hence, our analysis demonstrates that, as far as innovation intensive activities of the biotech industry are concerned, externalities associated with a particular network of organizational interactions operating within a tight geographic context stand out as a powerful form of technological relatedness and knowledge creation that channels city innovation.

Table 3.2: Log-likelihood for new product output of pharmaceutical and biotechnology industry

2009					2010					2011				
Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik
1	0.5	0.3	0.2	-456.343	1	0.6	0.2	0.2	-456.026	1	0.5	0.5	0	-444.200
2	0.5	0.4	0.1	-456.375	2	0.7	0.2	0.1	-456.801	2	0.6	0.3	0.1	-445.161
3	0.6	0.3	0.1	-456.941	3	0.8	0.1	0.1	-457.715	3	0.7	0.3	0	-445.853
4	0.6	0.2	0.2	-457.234	4	0.7	0	0.3	-456.983	4	0.7	0.2	0.1	-445.921
5	0.5	0.5	0	-457.445	5	0.6	0.3	0.1	-456.067	5	0.8	0.2	0	-446.716
6	0.5	0.2	0.3	-457.449	6	0.6	0	0.4	-456.379	6	0.8	0.1	0.1	-446.921
7	0.7	0.2	0.1	-457.666	7	0.9	0	0.1	-458.647	7	0.7	0	0.3	-447.103
8	0.6	0.4	0	-457.826	8	0.8	0.2	0	-457.678	8	0.6	0	0.4	-447.134
9	0.7	0.3	0	-458.242	9	0.8	0	0.2	-457.796	9	0.8	0	0.2	-447.398
10	0.4	0.2	0.4	-458.365	10	0.9	0.1	0	-458.569	10	0.9	0.1	0	-447.652

Table 3.3: Log-likelihood for gross output of pharmaceutical and biotechnology industry

2009					2010					2011				
Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik
1	0.9	0.1	0	-345.347	1	0.9	0.1	0	-320.677	1	0.8	0.2	0	-330.706
2	0.9	0	0.1	-345.430	2	0.9	0	0.1	-321.027	2	0.7	0.2	0.1	-330.939
3	0.8	0.1	0.1	-345.640	3	0.8	0.1	0.1	-321.081	3	0.7	0.3	0	-331.053
4	0.8	0.2	0	-345.825	4	0.8	0.2	0	-321.148	4	0.8	0.1	0.1	-331.189
5	0.7	0.2	0.1	-346.330	5	0.7	0.2	0.1	-321.809	5	0.9	0.1	0	-331.272
6	0.8	0	0.2	-346.482	6	0.8	0	0.2	-321.896	6	0.6	0.3	0.1	-331.631
7	0.7	0	0.3	-346.804	7	0.7	0.1	0.2	-322.237	7	0.9	0	0.1	-332.077
8	0.7	0.3	0	-346.804	8	0.7	0.3	0	-322.415	8	0.6	0.4	0	-332.210
9	0.7	0.1	0.2	-346.968	9	0.7	0	0.3	-322.999	9	0.7	0.1	0.2	-332.357
10	0.6	0.3	0.1	-347.541	10	0.6	0.2	0.2	-323.056	10	0.6	0.2	0.2	-332.500

In order to further investigate the types of spillovers that operate among cities and their circumstances, we study the estimation results for direct, indirect, and total effects. In the SDM model, we cannot interpret the partial derivatives as measures of impacts of predictors, as in the ordinary least-squares regression model. Thus, we use , the summary measures of direct, indirect, and total effects to evaluate the sign and magnitude of impacts on new product output that are determined by the changes in the explanatory variables. The direct effect provides a summary measure of the impact arising from changes in city *i* on the dependent variable in city *i*; the average indirect effect measures the impact of changes in neighboring city *j* on the changes of dependent variable in city *i*; the total effect includes both the direct and indirect effects (LeSage and Pace 2009). Indirect effects are able to detect flows of knowledge arising both from spatial proximity and organizational networks, which can be explained in two ways: one shows how changes from inputs in all other cities *j* impact region *i*, or how changes to region *i*'s inputs influence all other regions (Hazir et al. 2016). In Tables 3.4-3.7, we report coefficient estimates and direct, indirect, and total effects that are statistically significant at 1% for new product activity in the pharmaceutical and biotech industry. For benchmarking purposes, corresponding results for gross product activity are reported in Tables 3.8-3.11.

After decomposing the total effects into direct and indirect effects, we find that the mechanism of knowledge spillovers between cities is mainly supported by internal R&D investment. There is statistical evidence of indirect effects that associate a one per cent change in region *i*'s R&D input to new product creation over all cities with spatial proximity or network relations in the order of 1.458% in 2009 (Table 3.5) and 0.910% in 2010 (Table 3.6). However, as the only statistically significant evidence of indirect effects, the magnitude of this effect of internal R&D input is found largest in 2009 and decreasing quickly across the three years. In other words, knowledge spillovers of spatially proximate and organizationally related cities depend on continuous internal R&D investments, otherwise the spillover effects decline each year to zero. When it comes to gross production, contrarily, variables other than R&D expenditure also show strong statistical evidence for indirect effects (Tables 3.9-3.11). There are indirect effects arising from regional science expenditures and export (with a negative impact). It implies that local expenditures in science and R&D, and weak involvement in exports are the main knowledge spillover sources in production at spatially proximate and well networked cities. Unlike the significance of sustained investment in innovation, the role of internal R&D in gross production activities is increasing across the three years. This result is consistent with the nature of biotechnology revealed in previous findings that the industry fits the intensive R&D-based model (Malecki 2014).

Direct effects are found to be consistent with previous empirical results. For new product creation, we find *Science expenditure* in a city is the only factor that has a significant direct effect in each of the three years of study, while *Urbanization*, *Industrial Specialization* and *R&D investment* are significant twice, and *Export* are significant once (Tables 3.5, 3.6, and 3.7). Table 3.5 illustrates that a one per cent change in region *i*'s science expenditure will increase new products by 1.23%, which also reveals a very small feedback effect as it is slightly different from the coefficient of 1.25 in Table 3.4. Later, four variables present their strong statistical evidence for direct effects (Urbanization, Regional science expenditure, Specialization, and R&D) with a dominant influence arising from urbanization. By and large, the same set of strong and significant predictors have direct effect on gross production (Tables 3.9, 3.10, 3.11).

When it comes to the total effects on production, internal R&D investment is the only element that has a positive and significant impact on new product output in the industry, and this impact is short lived (two years) in our static scenario. Table 3.5 shows that, in 2009, a one percent change in R&D input increases new product output in region *i* by 1.61 per cent (an elasticity response because of the log-transformation), but this effect shrinks to 1.24 percent in 2010. The factors are much more broad-based when we look at gross production in the biotech industry as a whole. Here, three explanatory variables positively and significantly impact production across all three years. It is notable that a prominent role is played by regional science expenditures in 2009, whereas industrial specialization and the industry's R&D input become more vital in the following two years. Table 3.9 shows that, in 2009, a one percent change in regional science expenditures increases output in region *i* by 2.1 percent (an elasticity response because of the log-transformation), whereas R&D input in this industry is observed to have an increasingly higher impact in in 2010 and 2011 (Tables 3.10 and 3.11).

Table 3.4: Estimation results of new product output of the pharmaceutical and biotech industry

	2009		2010		2011	
Variable	Coef.	z-prob.	Coef.	z-prob.	Coef.	z-prob.
Constant	1.032	0.350	1.642	0.155	2.289	0.026
Urbanization	0.361	0.442	1.188	0.011	1.175	0.008
Human capital	-0.215	0.464	-0.524	0.072	-0.479	0.086
Science expenditure	1.251	0.000	1.063	0.000	1.003	0.000
Industrial diversity	-0.349	0.665	0.355	0.658	0.651	0.399
Specialization	0.365	0.241	0.867	0.005	0.944	0.001
R&D	0.135	0.099	0.313	0.000	0.283	0.000
Export	0.263	0.000	0.095	0.149	0.075	0.226
W-urbanization	1.192	0.400	0.381	0.771	1.833	0.149
W-human capital	-0.406	0.595	0.236	0.719	-0.670	0.376
W-science exp.	-1.683	0.016	-0.914	0.145	-0.101	0.866
W-industr. diversity	-1.450	0.556	-0.181	0.933	-0.902	0.705
W-specialization	0.427	0.613	0.038	0.959	0.401	0.603
W-R&D	0.849	0.005	0.402	0.118	0.311	0.276
W-export	-0.256	0.236	-0.205	0.272	-0.497	0.011
W-output	0.369	0.015	0.401	0.002	0.430	0.003
log likelihood	-456.343		-456.026		-444.200	
R-squared	0.419		0.371		0.396	

Table 3.5: Average marginal effects for new product output of the pharmaceutical and biotech industry, 2009

2009	direct effects	indirect effects	total effects
Science expenditure	1.226***	-1.990	-0.764
R&D	0.150	1.458**	1.609**
Export	0.261***	-0.261	0.000

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.6: Average marginal effects for new product output of the pharmaceutical and biotech industry, 2010

2010	direct effects	indirect effects	total effects
Urbanization	1.225**	1.342	2.567
Science expenditure	1.047***	-0.786	0.261
Specialization	0.889**	0.648	1.537
R&D	0.332***	0.910*	1.242**

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.7: Average marginal effects for new product output of the pharmaceutical and biotech industry, 2011

2011	direct effects	indirect effects	total effects
Urbanization	1.245**	4.336	5.582
Science expenditure	1.001***	0.646	1.647
Specialization	0.974**	1.437	2.411
R&D	0.294***	0.821	1.115

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.8: Estimation results of gross output of pharmaceutical and biotechnology industry

	2009		2010		2011	
Variable	Coef.	z-prob.	Coef.	z-prob.	Coef.	z-prob.
Constant	2.762	0.002	3.146	0.000	4.439	0.000
Urbanization	0.648	0.035	0.985	0.000	1.130	0.000
Human capital	0.352	0.065	0.041	0.815	-0.341	0.059
Science expenditure	0.597	0.000	0.640	0.000	0.686	0.000
Industrial diversity	0.145	0.783	0.212	0.660	0.762	0.126
Specialization	1.185	0.000	1.087	0.000	1.189	0.000
R&D	0.102	0.057	0.308	0.000	0.274	0.000
Export	0.125	0.003	0.023	0.558	0.001	0.987
W-urbanization	-0.144	0.820	0.074	0.901	-0.081	0.905
W-human capital	0.128	0.686	0.168	0.555	0.268	0.415
W-science exp.	0.768	0.011	0.441	0.106	0.155	0.610
W-industr. diversity	0.123	0.906	-0.336	0.725	1.021	0.351
W-specialization	-0.103	0.768	0.007	0.983	-0.353	0.339
W-R&D	0.331	0.003	0.375	0.001	0.370	0.003
W-export	-0.213	0.016	-0.102	0.209	-0.065	0.483
W-output	0.331	0.000	0.233	0.008	0.368	0.000
log likelihood	-345.347		-320.677		-330.706	
R-squared	0.535		0.576		0.549	

Table 3.9: Average marginal effects for gross output of pharmaceutical and biotechnology industry, 2009

2009	direct effects	indirect effects	total effects
Urbanization	0.656**	0.093	0.748
Science expenditure	0.662***	1.397**	2.059***
Specialization	1.191***	0.413	1.604**
R&D	0.122**	0.531**	0.653***
Export	0.114**	-0.253**	-0.139

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.10: Average marginal effects for gross output of pharmaceutical and biotechnology industry, 2010

2010	direct effects	indirect effects	total effects
Urbanization	0.995***	0.388	1.383
Science expenditure	0.667***	0.755**	1.422***
Specialization	1.095***	0.322	1.417**
R&D	0.328***	0.562***	0.889***

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.11: Average marginal effects for gross output of pharmaceutical and biotechnology industry, 2011

2011	direct effects	indirect effects	total effects
Urbanization	1.151***	0.487	1.638
Science expenditure	0.710***	0.639	1.349**
Specialization	1.208***	0.149	1.358**
R&D	0.298***	0.718***	1.015***

Notes: *** 99% confidence level, ** 95% confidence level.

To sum up, using new product output as dependent variable to capture the spillover effects from various indicators in the pharmaceutical and biotechnology industry, we see that spatial concentration is an important source of knowledge spillovers, but network externalities instilled by local interactions and interactions with proximate citied play a large and growing role. Innovation sets businesses apart since gross output is marked by the preponderance of proximity-induced effects and the absence of long-distance network effects. Finally, internal R&D investment is the sole source of indirect effects that transmit knowledge between organizationally related cities.

3.4.2. Spatial and network effects in the technology hardware and equipment industry

As innovation is fostered along different pathways across industries, we further investigate the space-time effects of spatial proximity and organizational networking for another high-tech industry, namely the technology hardware and equipment industry (including information and communication technology and semiconductors). Estimation results on innovation in the technology hardware and equipment industry are reported in Table 3.14, with the benchmark results for gross production in Table 3.18. Following the same research design as earlier, we report the different combinations of spatial weights for two measures of economic activities, new product output as an indicator of innovation and gross production as a benchmark. Several conclusions could be drawn from Tables 3.12 and 3.13. First, with the consideration of new product output as indicator of innovation, the best model fit is obtained when a large weight (70%) is assigned to distant network partners (W_3) and a small non-zero weight to spatially adjacent cities (W_2) since the second year in 2010 and continuing on for 2011. It explains the important role of organizational interactions taking place between distant cities in knowledge exchange in technology hardware and equipment industry. This is also consistent with the low impact (20%) of local externalities (W_1). The small weights used to express the impact of neighboring cities may point out that, with the importance of industrial specialization, a network stretching over long distances may be more functional in terms of knowledge flows to fulfill and increase the probability of creating new product than those of adjacent city pairs. In this industry, spatial proximity is of little value to incubating innovation so that businesses are intent on expanding organizationally wherever human talent effective at unleashing innovation is available. Second, the impact of the type of spillovers was drastically different in 2009, where the preponderance of effects was tied to spatial proximity (70%), with 30% pointing to long-distance networks and no effect of proximate networks. This suggests that 2009 was a year of transition of the industry, with a shift of emphasis from the geographic concentration to organizational networks operating at the scale of the national territory as the industry grew more mature. Third, overall output of the industry exhibited the reverse pattern over the same period, with the best model fit obtained with a large and growing weight (at least 80%) assigned to local interactions (*W_1*) and a small and dwindling weight for organizational network at long distance (20% and lower). Therefore, given the weights assigned to all three components, we conclude that organizational network beyond the spatial concentration is increasingly important for the value of new products in technology hardware and equipment industry, whereas more traditional production activities remain largely structured by spatial spillover effects.

Table 3.12: Log-likelihood of new product output of the technology hardware and equipment industry

2009					2010					2011				
Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik
1	0.7	0	0.3	-401.041	1	0.2	0.1	0.7	-418.331	1	0.2	0.1	0.7	-406.249
2	0.7	0.1	0.2	-401.071	2	0.2	0	0.8	-418.730	2	0.1	0	0.9	-406.332
3	0.8	0	0.2	-401.080	3	0.3	0	0.7	-418.771	3	0.2	0	0.8	-406.552
4	0.6	0.1	0.3	-401.087	4	0.5	0.1	0.4	-418.860	4	0.5	0.3	0.2	-408.031
5	0.6	0	0.4	-401.138	5	0.4	0	0.6	-418.966	5	0.5	0.2	0.3	-408.080
6	0.6	0.2	0.2	-401.206	6	0.5	0	0.5	-419.083	6	0.4	0.5	0.1	-408.134
7	0.5	0.1	0.4	-401.270	7	0.6	0	0.4	-419.133	7	0.5	0.1	0.4	-408.205
8	0.5	0.2	0.3	-401.285	8	0.3	0.6	0.1	-419.140	8	0.5	0	0.5	-408.294
9	0.8	0.1	0.1	-401.310	9	0.4	0.5	0.1	-419.145	9	0.3	0	0.7	-408.305
10	0.9	0	0.1	-401.334	10	0.5	0.4	0.1	-419.178	10	0.5	0.4	0.1	-408.307

Table 3.13: Log-likelihood of gross output of the technology hardware and equipment industry

2009					2010					2011				
Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik	Rank	λ_1	λ_2	λ_3	log-lik
1	0.8	0	0.2	-417.728	1	0.9	0	0.1	-409.719	1	0.9	0.1	0	-419.141
2	0.7	0	0.3	-417.736	2	0.9	0.1	0	-409.735	2	0.8	0.2	0	-419.178
3	0.6	0	0.4	-417.781	3	0.8	0	0.2	-409.807	3	0.7	0.3	0	-419.236
4	0.9	0	0.1	-417.820	4	0.7	0	0.3	-409.898	4	0.6	0.4	0	-419.378
5	0.5	0	0.5	-417.918	5	0.8	0.2	0	-409.901	5	0.5	0	0.5	-419.381
6	0.6	0.1	0.3	-418.167	6	0.8	0.1	0.1	-409.919	6	0.9	0	0.1	-419.452
7	0.5	0.1	0.4	-418.209	7	0.6	0	0.4	-410.065	7	0.8	0.1	0.1	-419.492
8	0.7	0.1	0.2	-418.226	8	0.7	0.1	0.2	-410.083	8	0.7	0.2	0.1	-419.552

9	0.8	0.1	0.1	-418.368	9	0.7	0.3	0	-410.162	9	0.6	0.1	0.3	-419.657
10	0.4	0.1	0.5	-418.484	10	0.7	0.2	0.1	-410.199	10	0.6	0.3	0.1	-419.657

Estimates for direct, indirect, and total effects on innovation are reported in order to more completely explain the spillover effects in this industry (Tables 3.15-3.17 and Tables 3.19-3.21). *Specialization* is the single indicator showing strong statistical evidence for indirect effects with a large positive impact on new product creation in technology hardware and equipment sector in 2010 and 2011. Given the strong network feature of this industry where a large proportion of the spillover weight is imputed to the long-distance organizational network, the prevailing indirect effect of industrial specialization unravels the unique spillovers of specialization between city pairs. It is worth noting this effect is not statistically significant in 2009 when spillovers are mainly local and that it amplifies between 2010 and 2011. Likewise, statistical evidence is also found on specialization as a channel of knowledge and technology spillovers in gross production (Tables 3.19-3.21), although the effect is weaker. Furthermore, *export* produces positive indirect effects on technology hardware and equipment products from the second year onward, but the same does not apply to new product output. In other words, being organizationally close to cities that are heavily involved in export of this specific industry may boost overall production, but not innovation or product derivatives. In general, our results are consistent with previous studies on the externalities of technological-related network that organizational proximity to region *i* is important to capture the spillover effects of industrial specialization

When focusing on direct effects, consistent results are once again observed for innovation and gross production. Table 3.15 and 3.16 show positive direct effects of four variables from 2009 to 2011 and these are *urbanization, regional science expenditure, internal R&D investment in the industry*, and *export.* Urbanization, as the indicator of market diversity and urban amenities, has a dominant impact on innovation in region *i*, but not on gross production in the industry. Small feedback effects are found for four variables. There is no enough statistical evidence of direct effects associated with industrial specialization in region *i*. In contrast, *specialization* produces direct effects in production activity.

The total effects (sum of direct and indirect effects) from a three-year view show that specialization and export keep generating significant and positive impacts both on innovation and gross production activity, although with different strength. For innovation, *export* shows a weakening effect over time, whereas *specialization* acquires the dominant role in industrial innovation from 2009 to 2011. Tables 3.15 & 3.16 indicate that one per cent change in *export* in technology hardware and equipment industry increases new product output in region *i* by 0.47 and 0.39 percent in 2009 and 2010, respectively. From 2010 to 2011, a much higher elasticity is obtained from *specialization* in Tables 3.16 and 3.17. The highest impact of *specialization* is observed in the third year (2011) that a one percent change increases new product output in region *i* by 1.32 percent. Overall, industrial export activity produces a quick but small effect, whereas specialization in this particular industry has an increasing and much bigger impact on new product activities, which can largely be imputed to spillover effects through the organizational network.

Table 3.14: Estimation results of new product output of technology hardware and equipment industry

	2009		bio2 output 2010		Gross output 2011	
Variable	Coef.	z-prob.	Coef.	z-prob.	Coef.	z-prob.
Constant	0.479	0.643	0.784	0.433	0.707	0.430
Urbanization	1.254	0.001	1.211	0.002	1.061	0.005
Human capital	-0.008	0.973	-0.067	0.797	-0.126	0.605
Science expenditure	0.736	0.001	0.835	0.000	0.739	0.001
Industrial diversity	0.644	0.324	-0.076	0.914	0.018	0.979
Specialization	0.098	0.297	0.131	0.200	0.121	0.208
R&D	0.317	0.000	0.379	0.000	0.345	0.000
Export	0.266	0.000	0.213	0.001	0.228	0.000
W-urbanization	-1.028	0.293	0.250	0.862	0.488	0.794
W-human capital	0.221	0.692	0.004	0.995	0.057	0.937
W-science input	-0.577	0.265	-0.890	0.262	-1.125	0.244
W-industr. diversity	-1.282	0.419	-1.230	0.585	-2.401	0.359

W-specialization	0.291	0.233	0.977	0.025	1.662	0.018
W-R&D	0.056	0.788	0.352	0.349	-0.046	0.939
W-export	0.021	0.877	0.243	0.296	0.277	0.439
W-output	0.375	0.001	-0.154	0.352	-0.384	0.037
log likelihood	-401.041		-418.966		-406.249	
R-squared	0.639		0.603		0.588	

Table 3.15: Average marginal effects for new product output of the technology hardware and equipment industry, 2009

2009	direct effects	indirect effects	total effects
Urbanization	1.236**	-0.907	0.329
Science expenditure	0.722**	-0.481	0.241
R&D	0.318***	0.258	0.577
Export	0.270***	0.198	0.468**

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.16: Average marginal effects for new product output of the technology hardware and equipment industry, 2010

2010	direct effects	indirect effects	total effects
Urbanization	1.221**	0.085	1.305
Science expenditure	0.830**	-0.894	-0.063
Specialization	0.129	0.839**	0.969**
R&D	0.378***	0.271	0.649
Export	0.213**	0.179	0.392**

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.17: Average marginal effects for new product output of the technology hardware and equipment industry, 2011

2011	direct effects	indirect effects	total effects
Urbanization	1.068**	0.052	1.120
Science expenditure	0.747 **	-1.053	-0.306
Specialization	0.105	1.219**	1.323**
R&D	0.346***	-0.102	0.244
Export	0.226**	0.128	0.355

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.18: Estimation results of gross output of technology hardware and equipment industry

	2009		bio2 output 2010		Gross output 2011	
variable	Coef.	z-prob.	Coef.	z-prob.	Coef.	z-prob.
Constant	0.953	0.412	1.257	0.277	1.774	0.148
Urbanization	0.155	0.097	0.828	0.028	0.788	0.047
Human capital	0.428	0.035	0.272	0.268	0.236	0.358
Science expenditure	0.871	0.000	0.641	0.004	0.565	0.015
Industrial diversity	-0.280	0.688	-0.091	0.891	0.318	0.647
Specialization	0.170	0.093	0.149	0.116	0.186	0.059

R&D	-0.047	0.529	0.156	0.029	0.165	0.027
Export	0.426	0.000	0.413	0.000	0.470	0.000
W-urbanization	0.442	0.639	-1.793	0.026	-1.664	0.047
W-human capital	-0.443	0.432	0.281	0.569	0.598	0.253
W-science input	-0.232	0.640	-0.385	0.354	-0.375	0.382
W-diversity	-0.347	0.822	0.247	0.851	1.539	0.259
W-specialization	0.664	0.004	0.426	0.031	0.402	0.050
W-R&D	-0.348	0.071	-0.218	0.180	-0.146	0.392
W-export	0.092	0.492	-0.013	0.909	0.043	0.718
W-output	0.146	0.168	0.491	0.000	0.359	0.000
log likelihood	-417.728		-409.719		-419.141	
R-squared	0.657		0.657		0.669	

Table 3.19: Average marginal effects for gross output of the technology hardware and equipment industry, 2009

2009	direct effects	indirect effects	total effects
Science expenditure	0.871***	-0.145	0.725
Specialization	0.186	0.796**	0.982**
Export	0.427***	0.175	0.602***

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.20: Average marginal effects for gross output of the technology hardware and equipment industry, 2010

2010	direct effects	indirect effects	total effects
Science expenditure	0.645**	-0.135	0.510
Specialization	0.198**	0.939**	1.137**
Export	0.431***	0.361**	0.792***

Notes: *** 99% confidence level, ** 95% confidence level.

Table 3.21: Average marginal effects for gross output of the technology hardware and equipment industry, 2011

2011	direct effects	indirect effects	total effects
Science expenditure	0.565**	-0.267	0.299
Specialization	0.217**	0.693**	0.910**
R&D	0.157**	-0.139	0.018
Export	0.483***	0.321**	0.805***

Notes: *** 99% confidence level, ** 95% confidence level.

3.5. Conclusions

Contemporary scholars regard industrial innovation and knowledge creation as the result of interactive learning processes both within and across firms to collaboratively solve particular production problems. Various theories have been proposed and discussed to better understand such processes. Our contribution is dedicated to overcoming the major myth in interpretation the local knowledge flows that were generally considered as the same of local knowledge externalities in earlier studies. This explanation overstates how much spatial constraints condition knowledge diffusion, while underestimating the role of other non-spatial forms of interactions such as the organizational network. In addition, the value and standard of innovation are not the same across the full spectrum of industries spanning from highly creative industries requiring fast-changing knowledge to slow-changing and more mature industries paying more attention to efficiency over creativity. Thus, the relationship between knowledge diffusion and innovation, on the one hand, and their modalities, on the other hand, is enhanced by a conceptualization that is sensitive to the context of each industrial sector, especially in knowledge-based industries.

In this research, we advanced a new way to support the theorization on the generative effects of interactions and organizational relations on innovation via knowledge flows by placing the city at its heart. We empirically examined the effects of knowledge diffusion of organizational networking on a city's innovation and production activities by taking into account that the innovation process involves learning in spatial concentrations as well as via city networks. These networks often support both physically and functionally proximate cities to learn and absorb knowledge from each other. Following the theoretical rationale of network externalities to innovation and production, we applied a spatial Durbin model to investigate high-tech manufacturing activities in two industrial sectors in 264 Chinese prefectural cities over the 2008-

2011 period. We used a framework that highlights interaction between cities as a hybrid combination of three spatial scales to address our research concerns on the relative significance of physical proximity versus broader city relations based on organizational networks.

Our findings suggest that the organizational network plays a role in transferring knowledge among cities, thus affecting both industrial activities of innovation and gross production output. However, extra attentions are required in explaining the effects and strengths for industries with different mode of knowledge creation and innovative activity, such as the two high-tech sectors in our study. For the pharmaceutical and biotechnology network, both proximate and distant interactions show a more extensive role in promoting new product activities than in gross production, but the effects of spatially proximate networks are only significant in the latter. Our results confirm the internal R&D investment as the only source of knowledge diffusion that flows among organizationally related cities with significant impact on city innovation. When further comparing the weights for proximate and distant networks of organizational cities, we find that the invention process of the biotech industry in *city i* takes advantage of knowledge exchange both from spatially proximate and distant neighbors only if there is a continuously high amount of interaction by means of internal R&D investment. For the technology hardware and equipment network, our findings suggest that spillover effects have shifted from being mostly based on spatial proximity to being driven by organizational network relations on great distance. Specifically, the organizational network affects innovative activity extensively through the flows of specialized employment at distant city pairs, whereas it has a small impact on gross production.

From a policy perspective, previous research on technological relatedness suggests that regions or countries could break technological trajectories and jump ahead by investing in building up external linkages (such as organizational network) and in their own innovation ability. Instead, we find that not all industries respond similarly and knowledge diffusion follows rather diverse spatial pathways through organizational networking, which depends on the core properties of pertinent knowledge and of the process of knowledge creation. The sharp differences found between the two high-tech sectors underscore that different types of knowledge bases may have different diffusion mechanisms. For industries that are in early development stages requiring tacit knowledge, such as biotechnologies, knowledge can be transferred both via short and long distance of the organizational network. However, the organizational flow of tacit knowledge requires continued investment by means of internal R&D input. Conversely, more mature industries with codified knowledge –like hardware and equipment industries-- are relatively insensitive to geographical distance; hence relations via distant organizational network play an important role in innovation. More importantly, although they are limited to a short time span, our spatial-temporal findings also suggest that the effectiveness of organizational connections in expanding innovative activities relies on distinct processes in two sectors. When the key element of innovation is the internal R&D investment in biotechnology, it requires a sustained investment to maintain the diffusion effects of organizational networks in promoting knowledge creation, otherwise such effects will decrease to zero shortly. In contrast, the organizational network of mature industries is strengthened by means of industrial specialization without the extra input each year.

Finally, this study points to further research opportunities along this line of work. First, consideration of local knowledge flows including pure geographical and non-geographical dimensions at the local level will provide us deeper understanding of how knowledge is transferred through various types of interactions so that the local knowledge externalities can be further explained. Second, data on other types of interactions, such as social and institutional, is expected to overcome limitations of the present study to unravel the link between knowledge diffusion and innovative activities. Third, comparing the modes of operation of domestic and foreign firms in the same economic space may reveal the risks and opportunities that contrasted familiarity with the domestic business environment may present. Finally, investigation covering a longer time period will allow us to develop a dynamic framework of knowledge creation and transformation, which will provide more evidence on building transformative innovation policy.

3.6. References

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CHAPTER 4 : MULTINATIONAL CORPORATIONS' LOCATION CHOICE IN KNOWLEDGE-BASED ECONOMY

In order to advance a new location choice theory, we argue that human capital or talent has become the primary determinant of location choice of high-tech multinational corporations in a knowledge-intensive economy. We apply a mixed discrete choice model to test hypothesis by estimating the relative importance of human capital, agglomeration and localization effects, and other traditional factors on firm location decisions. We use data from five leading economic regions of China. The findings are consistent with the hypothesis and show that human capital plays a much larger role than industrial localization in determining the location of high-tech multinational corporations.

4.1. Introduction

During the Fordist industrial era, industrial clusters were central to location decisions of corporations and their subsidiaries (Krugman 1990; Porter 2000). While industrial districts are considered an important feature in the traditional locational theory (Alonso 1960; Lösch 1954; Walter 1966) and while extensive efforts went into validating it with empirical evidence (Feldman and Audretsch 1999; Henderson 2003; McCann and Folta 2011; Nakamura 1985; Saxenian 2002), a radical shift in research has started to focus on the influence of talent and related factors building innovation ecosystem in the locational choice and spatial organization of firms in post-industrial capitalism. Meanwhile, the location choices of multinational corporations (MNCs) and their organizational changes have deeply altered the character of the world economy in recent decades (Nielsen, Asmussen, and Weatherall 2017). The recurrent state of flux in units of MNCs around the world, especially the high-skill corporate units, is of particular interest to corporate strategists and economic geographers as they seek to renew their theoretical understanding of the locational processes of knowledge-based firms. This research intersects these lines of inquiry and seeks to better articulate the circumstances where human capital stands as a determining factor in the location theory of knowledge-based MNC firms in post-industrial economies. The empirical analysis studies the location of 1,526 high-tech MNCs from five economic regions in China to test a web of three related hypotheses within a mixed discrete choice modeling framework.

In this vein, when it comes to the location choice of foreign direct investment (FDI), as for domestic enterprises, industrial districts have been the concept of reference. There has been intense scrutiny on the determinants of the location choice of FDI firms, such as the traditional factors including market size, taxes, industrial cluster, costs of inputs, international trade policies, exchange rate, infrastructure and so on (Alonso 1960; Blanc-Brude et al. 2014; Krugman 1979; Ohlin 1935; Vernon 1966). More recently, the emphasis has been drawn towards other considerations, among which the effect of economic institutions and cultural embeddedness of the host countries stands out (He and Zhu 2017; Nielsen et al. 2017). Economic institutions can be defined as the multiple components of institutions that provide opportunities and constraints to smooth the operation of a market economy. It includes contract enforcement, the legal system and government efficiency. The institutional viewpoint has been increasingly applied as a framework of business strategy (Dacin, Goodstein, and Scott 2002; North 1990) and the behavior of MNCs in particular (Du, Lu, and Tao 2008).

A recent debate in economic geography has sought to realign the respective merits of prevailing theories of industrial clustering and related theoretical extensions on economic and institutional structures (Florida 2003; Penco et al. 2020). It is particularly striking that contemporary firms are much more footloose in locating their corporate headquarters and branches. The relocation of operations of large companies presents several inconsistencies with the traditional theories, which brings to light that cost minimization is not the most important corporate strategy any more, but the composite of talent or human capital plays an increasingly significant role in orienting their location choices (Duranton and Puga 2005). Although the prominence of talent or human capital to the thriving of the modern knowledge-based economy has been extensively documented (for instance, Bell 1976; Drucker 1994; Machlup 1962; Simon 1998), it has been claimed that their role in the location and relocation of corporations necessitates a new paradigm in theory (Adler and Florida 2019).

By the same token, we argue that the essential differences between traditional and new paradigms of location choice theory lie in the basic assumption of the labor in the economic model. From the traditional theoretical view, labor is considered as the cost of production and can be replaced by capital in the production function (Roncaglia 2005). As a result, cost minimization is a key to increase profit in industrial era. However, in post-industrial economy, as knowledge is internalized in the labor, labor is not only irreplaceable but also heterogeneous. Therefore, our hypothesis, or theoretical conjecture, is that when knowledge plays a pivotal role which makes labor heterogeneous, talent or human capital is the primary consideration in location choice, when two labors possess the same skill-set or quality of knowledge, then firms might tend to choose a place with lower cost.

Drawing on the literature on the location choice of MNC units and their geographical implications, this research aims to advance the theory of MNCs' location choice in knowledge-based economies with a focus on human capital. We argue that, as talent or human capital has become a key factor of location and relocation of large corporations and headquarters, the location choices of high-skill MNC manufacturing units will favor places with large concentrations of human capital. We also test whether the economic institution helps to shape the location choices of high-tech MNC firms when considering the role of human capital. In addition, we look at cultural affinities as a factor of MNC location in a host country. Specifically, China as a host country of inward FDI encompasses a rich variety of sources, such as Taiwan, North America, Europe, Japan, and South Korea. Different FDI home countries display diverse cultural distances to mainland China. For example, Hong Kong and Taiwan substantively share the same culture as mainland China, while Europe and North America are more distant from the Chinese culture. Therefore, we try to expand the understanding of how the interactive between economic institutions and cultural distance shapes the location of high-tech firms from diverse countries and regions.

In this paper, therefore, we study the location of 1,526 high-tech MNC units in five economic regions in year 2008 to test these hypotheses. These MNCs are from five major countries and regions including Taiwan, Japan, South Korea, North America, and Europe. We estimate mixed discrete choice models that examine the relative importance of human capital, economic institution and cultural distance variables alongside measures that have been proposed in other studies of the determinants of location decision of MNC firms. The paper is structured as follows. The next section surveys the related location theories and discusses the empirical implications of competing theoretical frameworks. Then, data sources and the empirical methodology are described in the third section. Finally, we present our estimation results and discuss conclusions with directions for future studies.

4.2. Location, knowledge-based economy and MNCs

In order to explain the locational decision of multinational firms, a large body of theoretical arguments have been expanded (Faeth 2009). In attempting to disentangle the drivers of location choices of high-tech MNCs, we focus on the essential theories articulated in connection with the evolving character of global economies and business goals. International trade has been studied for centuries and its related theories have been advanced to understand the phenomenon of FDI in the early stages of foreign investments. In addition to the pure economic factors, theoretical perspectives of agglomeration and institutions were later introduced to reflect a broader range of effects related to destination location characteristics. Finally, as many of the existing explanations have failed to explain the location choices of high-tech MNCs in recent decades, we discuss a new location theory focusing on large and knowledge-based corporations, which supports the cornerstone theoretical argument of this research that human capital or talent is the primary determinant of the location choice of high-skill MNCs in knowledge-based economy.

Early studies on the economic interaction between countries were based on the classical trade theories of Ricardo (1871) and Ohlin (1933) and subsequent work specifically focusing on FDI was in the lineage of the New Trade Theory (Krugman 1979). In order to distinguish the location factors that have direct impact on business profits, research on ‘pure economic factors' mainly builds the FDI firm performance upon a cost and revenue model. On the costs side, most studies consider tax rate and physical infrastructure, as well as the wage levels; characteristics from destination location such as market size and human capital are on the revenue side behind FDI location choices. Overall, there are studies focusing on one or more of these variables, also others considering them as control variables (Faeth 2009).

In addition to the purely economic factors, attention has also been drawn towards three complex theoretical frameworks, namely industrial agglomeration, institutions, and global cities (Kim and Aguilera 2016; Nielsen et al. 2017). Since Marshall's seminal work, study on the nature of the agglomeration externalities across industries has been extensive (Krugman 1990; Porter 2000). Three dimensions are commonly recognized, namely industrial scope, geographic scope, and temporal scope. Industrial scope encompasses localization economies (also known as intra-industry agglomeration) and urbanization economies (known also as industrial clustering). The original agglomeration theory discusses how firms from the same industry clustered at the same location share knowledge and information, thus improving productivity. Therefore, irrespective of national sources, firms within the same industry supported by the geographic concentration could take advantage of knowledge spillover (Ciccone and Hall 1993; Krugman 1990; Rosenthal and Strange 2004). Thus, such theoretical perspective points to drivers of FDI location choice.

In contrast to agglomeration theory, the study of globalization implies that it reinforces both geographical patterns of international business activities and new forms of industrial organization that makes the former possible (He and Zhu 2017). Global cities, for example, have been argued to have a strong ability to attract FDI (Goerzen, Asmussen, and Nielsen 2013). In this frame, global cities are different in ways of exhibiting good interconnectedness to both the local and the global market with a cosmopolitan feature and clusters of advanced producer services (Sassen 2011). These arguments lead to the position that inflow FDI is more likely to choose a place as a destination where there is a higher level concentration of foreign firms (Nielsen et al. 2017). In this sense, globalization is viewed as one of the determinants for the uneven geographic distribution of FDI.

In spite of its continued overall prominence, agglomeration theory's ability to encapsulate the guiding principles of how large knowledge-based firms make their location decisions is waning. Under the classical paradigm for location choice, the leading strategy of a corporation is to minimize costs including labor, land, rent, and taxes. Agglomeration theory is effective at explaining the activities of small and medium-size firms and how they take advantage of horizontal linkages within the cluster. Nevertheless, it tends to understate the economic power and to overlook the prerogatives of large corporations, which may show heterogeneity in location choices (McCann and Folta 2011; Rigby 2015). For example, an empirical study by Mariotti, Piscitello, and Elia (2010) finds that multinational firms are more willing to agglomerate with other MNCs and tend not to agglomerate with domestic companies in order to prevent knowledge leaking to other firms in the cluster. More importantly, there has been an increasing change in the geography of corporations that the locations of modern knowledge-based firms are less restricted by cost considerations, but more often driven by access to high-skill worker or talent in knowledge-based capitalism. Therefore, it has been argued that there is a need to recognize the essential resources that large corporations search for in locations, thus building a new paradigm of such changing geography of large and knowledge-based firms in a post-industrial economy (Penco et al. 2020).

Among the related body of empirical studies, Adler and Florida (2019) provide strong evidence of the necessity of a new paradigm for location choice of knowledge-based corporations. In their research, they use the locations of corporate headquarters of the largest corporations on the well-known Fortune 500 list in 1955, 1975, 1996, 2000 and 2017, and find that headquarters location is mainly shaped by access to talent or human capital. Because human capital is unevenly clustered in certain cities and metropolitan areas, a firm will search for the desired specialization of the local labor force in order to keep up with specific competencies. In other words, knowledge-intensive firms will bear on relative higher costs in order to benefit from the source of human capital. As a result, larger corporations would ideally locate in a skilled city, which is usually a city with great access to universities and talent clusters (Adler and Florida 2019).

In line with the extensive literature documenting the pivotal role of human capital in the knowledge economy (for instance, Bell 1976; Drucker 1994; Powell and Snellman 2004), research on the new economic geography concurs to find that human capital growth is unevenly distributed in a small number of skilled cities with advantages in both consumption and production (Berry and Glaeser 2005; Shapiro 2006). Especially, a select set of industrial sectors in high-level technology, finance, corporate strategy and marketing - which are strategically important to large corporates and global multinational firms - are even more spatially concentrated (Duranton and Puga 2005). These competitive environments rich in knowledge and talent sought after by large firms are unevenly distributed in space. In the agglomeration theory, such skilled labor is regarded as human capital shared among the firms that belong to the cluster; however, knowledge required by large corporations and multinational firms is confined to a few cities, such as cities with access to university assets (Florida, Mellander, and Holgersson 2015). This implies that the dimension of location decisions of large and small firms is assumed to be contrasted (Adler and Florida 2019).

Although the new location theory mainly focuses on the geography of corporation headquarters of large firms, we argue for expanding the new theory and paradigm to encompass global MNCs location decisions. As knowledge has become the key element of long-term sustainable development across the world (Carrillo et al. 2014), by their nature, corporate headquarters and global MNCs share many similarities in location decisions and corporate strategy in the knowledge-based economy (Duranton and Puga 2005; Mariotti, Piscitello, and Elia 2010). Since specific kinds of talent or human capital are important to knowledge-intensive MNCs, seeking to prioritize human capital over costs has become a core strategy when choosing their unit locations in other countries. Taking China as an example, the location of MNCs' subsidiaries mainly concentrate in a few big cities where the costs of labor and land are higher than in the rest of the country. In 2008, 1,546 high-tech subsidiaries of global MNCs were located in only 54 large cities, which include both major urban centers such as Beijing and Shanghai as well as all the provincial capitals. We seek to unravel the essential resource these multinational firms are drawn to while considering where to locate among a potential set of over 300 Chinese cities.

In addition to factors of human capital and agglomeration, the literature identifies other factors that bear on the location choices of MNCs in other countries. From the theoretical perspective of new institutional economics, business transactions are reflected in firms' costs, for example, the cost of obtaining information and the contract writing and enforcing. Such costs can be reduced by the efficiency of institutional environments that provide the rules of interactions in societies and organizations (Coase 1937; North 1991). In the case of the MNCs' decision making, these costs can be minimized by an efficient institutional environment. Institutional environment broadly encompasses several dimensions: the state of contract enforcement, government intervention in business operation, and bureaucratic corruption based on the New Institutional Economics framework (Grosse and Trevino 2005). In general, beyond the traditional economic, political, and financial dimensions, an effective set of local institutions in both private and public sectors may help to improve firms' embeddedness and to reduce their possible relocation. A region featured poor economic institutions is often functioning with weak contract enforcement, insufficient protection of property rights, heavy government intervention and a bad reputation for corruption.

In principle, contract enforcement depending on the state of law enforcement and legal institutions could provide adequate protection on technology transfer and well-defined property rights for firms. The rigor of law enforcement is also closely intertwined with the role of government intervention in business operations. On the one hand, firms may find that government help is an alternative when the lack of properties protection and a weak court system are endemic. On the other hand, increased government involvement in business can easy evolve into rent-seeking and even corruption. The various models on how bureaucrats and entrepreneurs interact (Frye and Shleifer 1997) are quite enlightening in this respect. In the model of invisible-hand, the legal system is strong, government is well organized and generally free of corruption. Government function is restricted to providing basic public goods and some regulations while leaving most allocative decisions to the private sector. Court system is effective in dispute resolution. In the two alternative models of helping-hand and grabbing-hand, due to the large influence of government, there are rising of corruption and the ineffectiveness of courts. Under the helping-hand model, bureaucrats are intimately interacting with private economic activity by selectively supporting some firms, pursuing industrial policy and keeping close relationship with entrepreneurs. While the legal framework is deemphasized, bureaucrats adjudicate most disputes. Corruption exists but is relatively limited compared to the grabbing-hand model. Under the latter model, government has the strongest power to impose their will on business and there is no unified regulatory framework. Recently, empirical evidence finds that a U-shaped relationship exists between corruptions and each of the two models, where helping hand model shows higher level of corruption than grabbing hand (Petrou and Thanos 2014).

All international business relationships depend on communications and negotiations between people of different cultures (Chandler and Graham 2010). Communication efficiency is even more important when two countries are perceived to have large disparity in national cultural. As a result, the institutional environment is regarded as more influential for the success of in international markets. As for the case of China, while it has been suggested that government intervention in the form of a helping-hand might be appealing to culturally remote countries in reducing the communication costs, others have argued the opposite (Du, Lu, and Tao 2012). Hence, our analysis further tests the interplay between the role of institutions and cultural distance in attracting high-tech MNCs from different countries.

4.3. Estimation model and sample data

In support of our empirical analysis, the mixed discrete choice model (McFadden and Train 2000; Train 2009) is implemented to study the effects of key hypothesized factors while controlling for other variables acknowledged in the literature. Compared to McFadden's conditional logit choice model, the mixed logit model can fit random coefficients for alternative-specific variables. This enables to relax the assumption of independence of irrelevant alternatives (IIA), which leads to a model that is more general than the conditional logit model.

More specifically, the choice situation under study is that of an MNC choosing a location that yields the highest profit over any other possible city. Let y_{ij} be the profit of firm *i* operating in city *j*; it is assumed to be a function of observed attributes of locations:

$$y_{ij} = \beta_i x_{ij} + w_{ij} a + \varepsilon_{ij} \tag{4.1}$$

where β_i are random coefficients that vary over cities, and x_{ij} is a vector of location-specific variables of city *j* chosen by firm *i*. α are fixed coefficients on w_{ij-1}, a vector of location-specific variables. ε is a random term that follows a type I extreme value distribution. The mixed logit model estimates the parameters of $f(\beta)$, for example, if the random coefficients β_i follow a normal distribution, $\beta_i \sim N(\mu, \Sigma)$, then the mixed logit model estimates μ and Σ.

The probability of firm *i* locating in city *j* is the standard logistic probability integrated over the density $f(\beta)$,

$$P_{ij}=\int P_{ij}(\beta)f(\beta)\,d\beta \tag{4.2}$$

The location *j* chosen by firm *i* must offer the highest profit over all other possible regions,

$$P_{ij} = \text{Prob}\ \{y_{ij} \geq y_{ik}\} \text{ for all } k \neq j \tag{4.3}$$

$$= \{\beta_i x_{ij} + w_{ij}\alpha + \varepsilon_{ij} \geq \beta_i x_{ik} + w_{ik}\alpha + \varepsilon_{ik}\} \text{ for all } k \neq j$$

P_{ij} can be further simplified to the following logit expression:

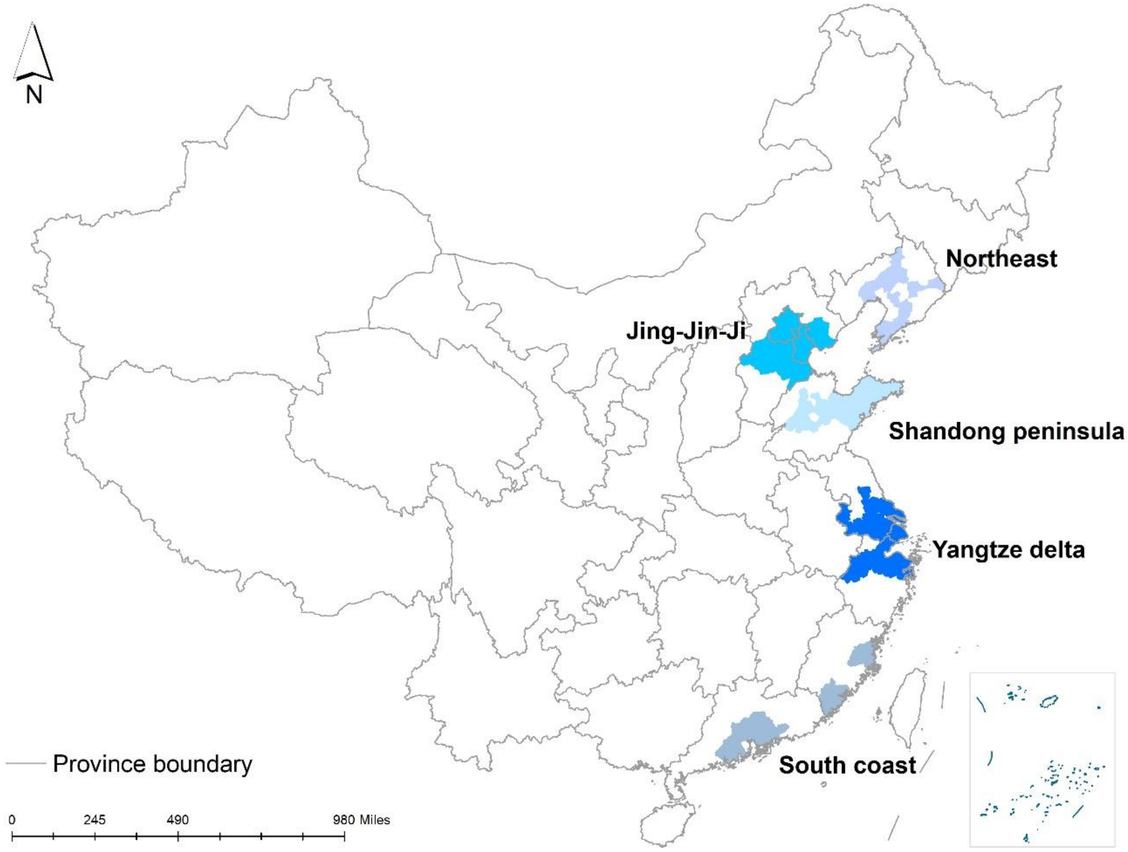
$$P_{ij}= \frac{e^{\beta_i x_{ij}+w_{ij}\alpha+\varepsilon_{ij}}}{\sum_{j=1}^{A} e^{\beta_i x_{ij}+w_{ij}\alpha+\varepsilon_{ij}}} \tag{4.4}$$

where A is the set of location choices faced by firm *i*. The model estimates how each city characteristic increases or decreases the chance that a city will be chosen rather than any other possible cities.

Our research focuses on high-tech MNCs in four subsectors: pharmaceuticals and biotech; office and computing machinery; radio, TV and communications equipment; as well as medical equipment, precision, and optical instruments. Also, to address a consistent set of choice considerations, we do not study the case of firms that are invested by foreign individuals, firms jointly owned by a Chinese government entity and some foreign company, nor firms set up with venture capital. Since there is no official data on the activities of high-tech MNCs in Chinese cities, we compiled data from the *China Industry Statistical Yearbook* (2008) according to the industrial code, types of holding and ownership of MNCs. First, we use the four-digit Standard Industrial Classification (SIC) code reported in the dataset to identify the high-tech firms in the four targeted subsectors. There are 19, 957 high-tech manufacturing firms including domestic, Taiwan, Hong

Kong, Macau, and foreign invested. Second, information on holdings and ownership allows us to identify firms co-owned or co-invested by the Chinese government and domestic corporations. After excluding these firms, approximately 4,000 firms are distinguished as fully invested by firms or individuals from Taiwan, Hong Kong, Macau, and other international countries. Third, we use the geographic location of each firm to aggregate at the city level for the further analysis. Despite having on hand information on holdings and ownership, our data source does not report the country origin of FDI firms. As a substitute, we used web scrapping to identify the country origin of each firm. In addition, we also searched each firm's public website to validate the ownership and national origin. After filtering out firms owned by foreign individuals and invested by venture capital, the sample is further reduced to 1,743 establishments in 121 cities.

To understand the location decision factors of high-tech MNCs in knowledge-based economies, we focus on MNC units from the five most important MNC source countries/regions in five major urban regions of China. The analysis is conducted on the subset of the broader sample that is comprised of 1,526 high-tech MNCs out of 1,743 high-tech establishments that originate from Taiwan, North America (US and Canada), Europe (EU and associated countries), Japan and South Korea, and are located in the following five leading economic regions: the Yangtze river delta, the South Coast, the Shandong peninsula, the Jing-Jin-Ji Metropolitan Region (Beijing-Tianjin-Hebei), and the Northeast. Fig. 4.1 presents the geography of the five regions as well as the 37 cities they are comprised of. The distribution of MNCs by country of origin and by Chinese regions is shown in Table 4.1. As described in the table, the Yangtze delta region contains the largest number of the MNCs (53%) in our sample and 77% of MNCs in total are located in the regions of the Yangtze delta and the South Coast.



Region	Cities					
Yangtze delta	Suzhou	Shanghai	Wuxi	Hangzhou	Ningbo	Changzhou
	Nanjing	Jiaxing	Nantong	Taizhou	Shaoxing	
South coast	Xiamen	Fuzhou	Zhangzhou	Shenzhen	Dongguan	Guangzhou
	Huizhou	Foshan	Jiangmen	Zhuhai		
Shandong peninsula	Qingdao	Weihai	Yantai	Jinan	Tai'an	Weifang
	Zibo					
Jing-Jin-Ji	Beijing	Tianjin	Langfang	Baoding	Cangzhou	Tangshan
Northeast	Dalian	Shenyang	Anshan			

Figure 4.1: Map of 5 regions as location of MNCs

Table 4.1: Distribution of high-tech MNCs across 5 regions in China

	North America	Europe	Japan	South Korea	Taiwan
Yangtze delta	105	149	244	27	288
South coast	51	48	82	19	159
Shandong peninsula	9	15	15	86	7
Jing-Jin-Ji	32	48	32	37	10
Northeast	2	10	33	8	3

The main independent variables that enable us to test the research questions presented in the introduction of this article include factors of human capital, public institutions, and cultural distance. These variables are now discussed, followed by several control variables that assure a well specified model.

As a measurement of human capital in each region, we aim to take the talent pool associated with innovation and knowledge creation at the best institutions of higher learning. Empirical work on this topic has often relied on measures of undergraduate students or above the bachelor degree. These measures can be underestimated, particularly across industries, and are at different levels of analysis. This paper uses as a proxy the number of full-time faculty members (from lecturer to professor) weighted with so-called 211-project institutions in the region. A select number of flagship provincial universities received this designation in 1995 for the purpose of further strengthening their research standing and accelerating their growth through a prioritization of public financial support. Therefore, the human capital level of a region is given by:

$$\text{Human capital}_i = \text{Log}\ [\ (T_i\ /\ t_i) * p_i] \tag{4.5}$$

where T_i is the total number of full-time faculty members (from lecturer to professor) in region *i*, t_i is the total number of institutions of higher education in that region, and p_i is the total number of 211-project institutions in each region ($p_i < t_i$). The list of 211-project institutions is obtained from the website of Ministry of Education of PRC. T_i and t_i are sourced from the *Statistical Yearbook of Chinese Cities 2008*.

The second set of variables pertains to public institutions and their impact on business practices; it is secured from the *Investment Climate Survey (ICS) 2005* conducted by the World

Bank[1]. Based on the face-to-face interviews with managers of sampled private firms in the manufacturing industry, the ICS aims to provide a range of qualitative and quantitative information. The purpose of this survey is to track changes in the business environment in the private sector over time. This survey has been conducted twice (2005 and 2012) with questions on the company's operations and growth, and business relations with clients and local administrations, and so on. The sample of interviewed firms was selected using stratified random sampling according to industry, establishment size, and geographic region. Only the 2005 survey is used because firms in a more limited number of cities were surveyed in 2012. The 2005 sample included 10,042 manufacturing firms in 120 prefectural cities; among these, 990 firms are from Hong Kong, Macau, and Taiwan and 1,398 enterprises are from other foreign countries. Given our concern with economic institutions and cultural differences, we only use the feedback from the latter 2,388 establishments to apprehend the business environment faced by MNCs in China; responses are aggregated to regions according to their city location. Thus, we select the *ICS* questions pertaining to the relationship with other companies and with government agencies, particularly those with local jurisdiction.

As legal institutions and law enforcement are the key components, we construct an indicator on business contract enforcement based on two questions on the ICS survey addressing this matter. From the question on *'the percentage that employed lawsuit to resolve business disputes'*, we obtain the average proportion of cases where a lawsuit is used to resolve disputes between a company and their dealers/clients and suppliers for each region. Next, the proportion is weighted by the average confidence companies have in the local legal system, which is obtained from the question *"In the case of commercial disputes with the suppliers, clients or subsidiaries*

[1] https://microdata.worldbank.org/index.php/catalog/602

in your province, how much confidence do you have that the disputes will be settled with justice by the local legal system?" (Percentage from 0 to 100). As shown in Table 2, the minimum value of 6.779% is from the Shandong peninsula whereas the Yangtze region shows the largest value on the measure of business contract enforcement, with 8.603%.

The indicator of government intervention in the management and operation of the businesses is also constructed on the ICS survey data. In the survey, there is a question asking *"how much autonomy management has over each of the three aspects of production, investment, employment without government interferences (1=0-19%; 2=20-39%; 3=40-59%; 4=60-69%; 5=70-79%; 6=80-89%; 7=90-99%; 8=100%)."* We use this question to construct the measurement of government intervention in each region. First, the average score on each of the dimensions of production, investment, employment is calculated for each region; second, the three scores are summed and used as the overall score of government intervention; third, to facilitate interpretation, we inverse the measurement scale by subtraction the score from the maximum of 24 (8 for each dimension). As a result, the higher the indicator, the more government intervenes in business practices in the region. The highest score of government intervention is 3.214 for the Northeast region, whereas the lowest of score of 1.709 is in the Shandong peninsula (as shown in Table 4.2).

The notion of corruption encompasses a tremendous complexity and it is apprehended differently according to the national culture (Chandler and Graham 2010). Given data availability, we focus on the risk of rent-seeking and construct a score based on two ICS questions. The first score counts the number of firms that had loans using the question *"Do you have loans from banks or other financial institutions"* while the second gives the number of firms that *"need to make informal payment to staff from the banks or lending institutions"*. We calculate the proportion of firms having loans in each region that made informal payments weighted by the percentage of informal payments in each region out the total informal payment of five regions. As presented in Table 4.2, the highest score on rent-seeking is 0.10 (in the Shandong peninsula) and the lowest score of 0.05 is in the Yangtze delta region.

We adopt Hofstede's (2011) cultural values framework to account for the cultural differences between MNC home countries and China. The Hofstede model[2] provides comprehensive insight on working values influenced by national culture, which has been widely applied in both academic and management settings. It consists of six dimensions that distinguish countries; the score for each dimension ranges from 0 to 100. These six dimensions include: (1). power distance index (PDI), illustrating how a society handles inequalities among people; (2). Individualism versus collectivism (IDV), which denotes how loosely-knit the social fabric is; (3). Masculinity versus femininity (MAS), representing preferences for achievement and cooperation; (4). Uncertainty avoidance index (UAI), expressing how a society copes with the inherent unpredictability of the future; (5). Long-term orientation versus short-term normative orientation (LTO), addressing societies' horizon when planning for the future; and (6). Indulgence versus restraint (IVR). Based on the scores of Hofstede's six dimensions, the cultural difference between two countries is calculated by the following function (Ng, Lee, and Soutar 2007):

$$\mathrm{CD} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{6}\{(\mathrm{I_{iA}}\text{-}\mathrm{I_{iB}})^2/\mathrm{V_i}\} \tag{4.6}$$

where CD is the cultural distance between countries *A* and *B*, $\mathrm{I_{iA}}$ is Hofstede's score on $\mathrm{i^{th}}$ dimension of country *A* and $\mathrm{I_{iB}}$ is the same dimensional score of country *B*. $\mathrm{V_i}$ is the score variance of all study countries on the $\mathrm{i^{th}}$ dimension, and *n* (here *n*=6) is the number of cultural dimensions.

[2] https://www.hofstede-insights.com/models/national-culture/

For the European countries, we first calculate the CD for each country between China, including France, Germany, Switzerland, Denmark, United Kingdom, Sweden, Netherlands, Italy, Spain, Norway, Finland, Austria, and Belgium. Then, the values are weighted by the 2008 population of each European country based on the data from World Bank. As a result, the arithmetic average value of CD = 4.015 is used for the overall cultural distance between Europe and China. Similarly, the arithmetic average value of CD of North America, including U.S. and Canada, is 4.747. At last, the CD between China and Japan, South Korea, and Taiwan are 2.307, 1.491, and 1.315, respectively. Although physical distance can reasonably be expected to be influential in the sheer magnitude of the cultural distances between two countries, there is no consensus on how to measure the physical distances between any two countries/regions (particularly large ones like the United States and China), which may further lead to the misspecification of the spatial dependence structure in the model. Therefore, our measurement of cultural distance is assumed to subsume the correlation between geographic and cultural distances.

In addition, for a fully specified model, we also include several control variables. First, we add a variable of industrial structure. Specifically, the location quotient (LQ) of employment in the studied 4-digit high-tech manufacturing sectors measures the high-tech industrial localization across the five regions:

$$LQ=(e_{ir}/e_r)/(E_i/E) \tag{4.7}$$

where e_{ir} is the employment in region *r* in 4-digit high-tech sector *i*, e_r is the employment in region *i* in all industries, E_i is the employment of all five regions in the same high-tech sector *i*, and E is the total employment of the five regions in all industries.

We also consider the effect of the agglomeration of MNCs from the same home region in Chinese urban regions on the location decisions of firms:

$$\text{Agglomeration\_MNCs}_{rm} = (n_{mr}/n_r) / (N_m / N) \tag{4.8}$$

where n_{mr} is the number of high-tech firms from home country *m* in region *r*, n_r is the number of high-tech MNC units in region *r*, N_m is the total number of high-tech units from home country *m* across all five urban regions, and N is the total number of high-tech MNC units of all regions.

Finally, we include the annual volume of civil aviation passenger traffic (10k people) at all airports in a region, which is sourced from the *Statistical Yearbook of Chinese Cities 2008*, to indicate the importance of airport infrastructure in support of the knowledge-based economy.

Table 4.2: Descriptive statistics on variables

Variable	Mean	Std. Deviation	Minimum	Maximum
Human capital	3.949	0.398	3.450	4.334
Economic institutions				
Contract enforcement	7.532	0.742	6.779	8.603
Government intervention	2.567	0.781	1.709	3.214
Regional corruption	0.072	0.017	0.054	0.096
Cultural distance	2.775	1.535	1.315	4.747
Localization	0.902	0.122	0.771	1.034
Agglomeration_home				
Europe	0.760	0.452	0.272	1.432
North America	0.396	0.303	0.066	0.805
Japan	0.438	0.317	0.105	0.922
Taiwan	0.350	0.425	0.042	0.939
South Korea	2.189	1.978	0.859	5.552
Airport	5.886	0.768	4.746	6.622

4.4. Results

Table 4.3 presents the results of our statistical analysis of the high-tech MNCs' location choices among urban regions of China and of their determinants. To alleviate the effects of multicollinearity when the three institutional indicators are jointly used as predictors in the model (variance inflation factor over 2), we study the influence of these factors via three separate models of location choices, with one institutional indicator in each. Except for one parameter that is not significant at 90%, all other estimates are statistically significant at the 95% confidence level or higher. Table 4.4 further estimates the direct marginal effects of each indicator on the predicted probabilities across the five urban regions. In other words, they indicate how the probability of choosing one region changes with the change of each region-specific variable. Our core hypothesis is that the geography of knowledge-based MNC firms in Chinese cities is determined by concentration of human capital. We are also interested in how the cultural distance between the MNC home country and mainland China impacts the location decision of MNCs in China in response to local economic institutions.

Estimation results show that human capital is a statistically significant factor of MNC location choices, and its effect is positive; in other words, the higher the concentration of human capital in an urban region, the more likely this region is selected by an MNC, all other factors being held constant. The evidence in Table 4.4 also indicates that human capital has the largest marginal effect on the probability of choosing a region over any of the others among all the factors considered. This is in fact a very general result of our analysis as it applies to all five urban regions under the three model specifications tested. Furthermore, the marginal effects of human capital and localization can be compared to evaluate the relative merit of the human capital hypothesis against the traditional perspective rooted in localization effects. Estimation results in Table 4.4 show that the impact of human capital always exceeds that of localization. It does so by a wide margin that can be as high as fivefold, particularly with model specifications (1) and (3). In the Yangtze delta region, the estimate of the direct average marginal effect of human capital taking government intervention into account (Model (1)) shows the highest value of 0.802 across the table, indicating a sharp and positive response in the probability of choosing this region if human capital in this region increases. The marginal effect of human capital is noticeably lower for the

South coast region (0.612 in model (1)), and even more so in the remaining three regions (ranging between 0.326 and 0.122). These trends carry over to the other models. It conveys the equilibrium development mode of human capital both in quantity and quality in the Yangtze region compared to other regions, which in turn helps to build a better environment and opportunity of collaboration and cooperation for companies in the region. Overall, with various economic institutions effects accounted for, human capital remains the factor with the strongest direct effect in each region. In this respect, our results indicate that as the essential structure of the economy has drifted towards knowledge-based activities globally, access to human capital has become pivotal for high-skill corporations and such a transformation now molds the location choices of MNCs in other countries. The empirical evidence provided by the model strongly supports that the probability of a high-tech MNC choosing a place to do business increases as human capital expands.

Government intervention in business practices has a positive impact on MNC location decisions, whereas the interaction between government intervention and cultural distance influences negatively. It demonstrates that regional government intervention in business is valued by MNCs and helps attract MNC business units, but also that its effect is weaker for MNCs from home countries/regions that are culturally more distinct from mainland China. In other words, local bureaucrats in China are perceived overall as extending a helping hand in business operations, such as nurturing a supportive business environment for MNCs and promoting their entry. The South coast and the Yangtze region are better positioned to capitalize on bureaucratic interventionism than other regions (Table 4.4). However, the success at turning these interventions into the entry of high-tech MNCs varies according to the source country. MNCs from countries/regions with closer cultural affinities more readily take advantage of government interventions than those MNCs from source countries/regions further away from China. Because of bureaucratic interventions, the South coast and the Yangtze region are more likely to lose out than other regions when seeking to attract business from more culturally different countries.

As hypothesized, for high-tech firms, contract enforcement shows a positive impact on MNC entry in an urban region. As stringent contract enforcement hinges on the dependable business environment framed by legal institutions and law enforcement, it significantly affects the location choices of knowledge-based MNC corporations. However, the marginal effect of contract enforcement is very small in all urban regions. In addition, the non-significant interaction term between contract enforcement and cultural distance suggests that the stringency of contract enforcement is equally influential for all high-tech MNCs across the various country sources.

Besides, our findings on corruption are mixed. First, overall, corruption has a significant negative impact that deters high-tech MNC entry in an urban region. However, given the positive role of the interplay between corruption and cultural distance, we find that MNCs from countries with close cultural affinities with mainland China are more sensitive to corruption than others, and adjust their locational decisions accordingly. In other words, western countries from Europe and North America show less concern for a culture of corruption in a region. Interestingly, prior research found the link between corruption and FDI to be ambivalent. Studies have reported results in opposite directions. From one body of research, it has been argued that since the US Foreign Corrupt Practices Act (FCPA) passed in 1977 and with similar restrictions on bribery in the Organization for Economic Cooperation and Development (OECD), the corruptibility of foreign government officials would have no effect on the differential attractiveness of countries (Chandler and Graham 2010). Another stream of research (Egger and Winner 2005; Leff 1964) holds the opposite view that practice of corruption acts has been adopted by many large MNCs since the late 1990s in order to gain access to the foreign market (such as the Chinese market). We find that

MNCs with cultural affinities with China shy away from corruption, but more western minded MNCs tend to espouse that corruption may be good for their business, as articulated by the second view on corruption.

Also, the choice model shows that MNC firms are more likely to co-locate with other high-tech establishments from the same home country. As it has been suggested by the literature, the clustering of foreign firms from the same home country/region helps to transform information into business practices and to share experience, thus accelerating the procedure of new entries to the new business environment. On the other hand, the statistical analysis found no support for an agglomeration effect with domestic firms (results are not reported in Table 4.3 because they are not statistically significant). Thus, we can say there is preponderance of evidence that MNC high-tech firms make a deliberate choice to co-locate with other MNC high-tech firms. Finally, a body of literature argues that, as the structure of the economy shifts from industrial to post-industrial, airport connectivity may play a more important role than highway for knowledge-based large corporations. Our results support that airport connectivity has a statistically significant and positive impact on high-tech MNCs entry, although marginal effects are usually weak. We also tested the factor of highway infrastructure and it is not significant in any of the models (results not reported in Table 4.3).

Table 4.3: Results of mixed logit choice models

Variables	(1)	(2)	(3)
Human capital	3.471***	1.992***	1.480***
	(0.319)	(0.129)	(0.180)
Economic institution			
Government intervention in business	1.189***		
	(0.239)		
Government intervention in business * cultural	-		

distance	0.097**		
	(0.056)		
Contract enforcement		0.761***	
		(0.209)	
Contract enforcement * cultural distance		0.044	
		(0.031)	
Regional corruption			- 0.581***
			(0.084)
Regional corruption * cultural distance			0.123***
			(0.020)
Localization	0.762***	0.987***	0.453**
	(0.057)	(0.067)	(0.191)
Agglomeration effects			
Agglomeration_home	0.758***	0.741***	0.876***
	(0.045)	(0.046)	(0.053)
Airport	0.810***	0.352**	0.151**
	(0.123)	(0.085)	(0.086)
No. of choosers	1,526	1,526	1,526
No. of choices	5	5	5
Wald Chi^2	1056.51	1047.84	1011.54
Log pseudo-likelihood	-1719.31	-1720.34	-1703.00

Notes: *** 99% confidence level, ** 95% confidence level, * 90% confidence level.

Table 4.4: Average marginal effects

	Jing-Jin-Ji	Northeast	South coast	Yangtze delta	Shandong peninsula
Model (1)					
Human capital	0.326***	0.122***	0.612***	0.802***	0.182***
Government intervention in business	0.087***	0.034***	0.167***	0.217***	0.052***
Government intervention in business * cultural distance	-0.018*	-0.011*	-0.043*	-0.042*	-0.009*
Localization	0.068***	0.026***	0.128***	0.168***	0.038***
Agglomeration_home	0.071***	0.027***	0.134***	0.175***	0.040***
Airport	0.076***	0.029***	0.143***	0.187***	0.043***
Model (2)					
Human capital	0.187***	0.070***	0.352***	0.462***	0.104***
Contract enforcement	0.019***	0.007***	0.035***	0.047***	0.010***
Contract enforcement * cultural distance	0.020	0.009	0.032	0.048	0.009
Localization	0.093***	0.035***	0.174***	0.229***	0.051***
Agglomeration_home	0.070***	0.026***	0.132***	0.173***	0.039***
Airport	0.015***	0.006***	0.029***	0.038***	0.008***
Model (3)					
Human capital	0.136***	0.052***	0.262***	0.341***	0.078***
Corruption	-0.020***	-0.009***	-0.048***	-0.060***	-0.015***
Corruption * cultural distance	0.089***	0.030***	0.132***	0.153***	0.062***
Localization	0.042***	0.016***	0.080***	0.105***	0.024***
Agglomeration_home	0.081***	0.031***	0.155***	0.202***	0.046***
Airport	0.014*	0.005*	0.028*	0.035*	0.008*

*** 99% confidence level, ** 95% confidence level, * 90% confidence level.

4.5. Conclusions

In this study, we contributed to the advancement of a new theory of the location choice and geography of high-tech manufacturing multinationals. We argued that, as the system of the economy has gradually shifted toward post-industrial and knowledge-based, close to talent and human capital has become more compelling for the location decision of high-tech MNCs, with a solid cadre of economic institutions playing a complementary role. The combination of these two can be a primary source of sustainable advantages of competition and cooperation for a region. Based on a dataset on the location of 1,526 high-tech manufacturing units of MNCs in mainland China, we tested our hypothesis using a mixed discrete choice model.

Our analysis confirms the primary thinking that knowledge-based MNCs show a strong tendency towards locating their high-tech manufacturing firms in places with great access to talent or human capital. Human capital is consistently positive and significant in our statistical models. Although localization still matters in manufacturing, when the magnitude of factors of human capital and industrial localization are compared, human capital is revealed to have a much greater impact over industrial localization on the location of high-skill large corporations. Our analysis is based on 2008 data, and we anticipate that such effect has amplified over the years in line with the increasing knowledge orientation of many manufacturing businesses. This is broadly consistent with our core argument and logic of the new location theory. Large knowledge-based firms do not need to follow the same ecosystems as much as smaller firms do. In the history of location theory, emphasis has mainly been on industrial clusters or on agglomeration for the purpose of increasing returns, whereas human capital is only considered as a control variable for the purpose of building a theoretical model of the space economy. Our contention is that a fundamental change is needed to develop new theoretical frameworks that accommodate the era of the knowledge economy. Our empirical analysis provides sound evidence of the shift on economic principles structuring the space economy and that location theory needs to develop further along this line of recognizing the specific nature of knowledge-intensive corporations in location theory. Our analysis also determined that airport connectivity is an important urban asset; it is a significant factor that is positively and consistently associated with the location of high-tech MNCs. As a vital piece of infrastructure, airports are a critical component from the perspective of the location theory of knowledge-intensive economic activities, in contrast to highways that are featured in the traditional location theory.

Economic institutions and their interaction with cultural distance also matter in the location choices of MNC high-tech firms. Using data on 1,526 MNC units from five major source regions, we find that contract enforcement has a significantly positive impact on all MNCs from different countries and regions whereas government intervention is seen as much more attractive to MNCs from countries with stronger cultural affinities. When government intervention extends as a helping hand, it not only attracts business but more importantly increases the magnitude of marginal effects of human capital. The negative interplay between government intervention and cultural distance raises future questions on the effectiveness of governments when dealing with different countries and regions. Furthermore, corruption is perceived quite differently depending on the origin of the MNC, with culturally close countries shying away while others welcome it. This appeal for rent-seeking or corruption by more western-minded MNCs calls for further investigation. Overall, the quality of economic institutions not only has impact on location choices but, more importantly, it affects the magnitude of human capital as the most influential factor in the knowledge-intensive economy. Research with longitudinal data can further enhance our understanding of how deeply these factors shape regional economic characteristics.

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CHAPTER 5 : CONCLUSIONS

In the introductory chapter of the dissertation, I pointed out that the evolution of economic activities, high-tech manufacturing in particular, challenge our understanding of contemporary theories and require us to revamp the conceptual foundations of theoretical models now in use. This means following the process of examination of current complex theories and abstraction underlying models with better evaluation. What conclusions does this lead us to at the end of the journey?

Three main motivations were taken into account before dealing with the research questions. The first aspect was to contribute to corroborate the theoretical conjecture regarding city network based on the economic foundation through empirical validation. The second was to empirically measure the advantages cities achieve from networking behavior by building a conceptual framework with related schools of thought on innovation and knowledge creation. The third was to advance the new theory of location choice in the era of knowledge-based economy, where traditional theories have diminishing explanatory power.

The first aspect from Chapter two provided a corroboration of the underlying theory of systems of cities from the network perspective. Based on the two complementary methods of network degree centrality and its ranking, and of meso-scale network structure modeling, we successfully identified the two theoretically conceptualized forms of network: complementarity network and synergy network. Theoretically, complementarity network and synergy network are two types of organizational logic of the city-system abstracted from the micro-level behavior of firms or individuals. These structures were hypothesized to serve different economic purposes as they apply to different sectoral specificities. While complementarity network describes economies of specialization and division of labor, which could be found in manufacturing cities, synergy network addresses economies of scale and innovative cooperation of cities with similar size, such as in the financial city network. Given the complex behavior of high-tech firms, our purpose was to provide precise insights into the organizational logics and the structure of city networks with empirical evidence.

Using 2008 firm-level data for three high-tech manufacturing sectors, our main conclusions of this chapter were as follows. First, city networks present variations in comparison with different high-tech sectors. Medium-sized cities in the Yangtze River Delta and Pearl River Delta regions present higher-order in the computing machinery and technological equipment sector, whereas some cities from the western and northeastern regions have disproportionately higher rankings for pharmaceuticals and biotech. Second, we found evidence of both the complementarity network and the synergy network in high-tech manufacturing cities. This not only supports the theoretical principle of the coexistence of two types of organizational logic of the city system, but also uncovers the fact that a synergy network exists also in high-tech manufacturing cities, which was mainly found in financial and service cities so far. Third, our results suggest that the city network reflected in high-tech manufacturing has a hybrid CP structure with regional communities. In addition, the core contribution regarding the geographic distance is that cities both from same and from different orders of functions are interconnected over long geographic distances, which breaks the premise of central place theory that a high-order city only interacts with its proximal hinterland. Our conclusions are based on the economic rationale of high-tech manufacturing activities over a single year; more empirical analysis with longitudinal data will further improve our understanding of the spatio-temporal evolution of city networks.

In the preceding chapter, we sought to foster new and more critical ways of theorizing relational and network thinking across spatial scales, as well as transformative change in innovation policy. To this end, we developed a conceptual framework that breaks the fragmentation of economic theories on industrial clustering, organizational networking and technological relatedness. All boiled down to headquarter and subsidiary relations to assess their impacts on knowledge creation by placing the city at the heart of this process. Based on the activities of two sub-sectors of high-tech manufacturing from 264 Chinese prefectural cities between 2008 and 2011, our empirical evidence focuses on statistically quantifying the respective roles of geographic proximity and organizational networks defined by the headquarters-subsidiaries relationships in fostering innovation in cities using the spatial approach that takes into account the co-existence of local clusters and organizational city network across spatial scales of proximate and distant.

Empirical evidence based on a new data set on Chinese cities and high-tech industries was used to test the effectiveness of theories on different types of knowledge and industrial modes – from fast- (biotech) to slow-changing (technology hardware and equipment) knowledge-based sectors. We found that knowledge diffusion along the organizational network has significant impacts on both innovation and production. However, the effects and strengths are strikingly different for the two high-tech sectors under study. In industries in early stage of development, where tacit knowledge is paramount, it is more effective with spatially proximate collaborations that allow face-to-face contact, co-presence and co-location of people and firms to accelerate knowledge creation. In contrast, in industries with codified knowledge, like hardware and equipment, emphasizing efficiency over creativity, the spillover effects of the organizational network are insensitive to physical distant. Compared to the previous findings on knowledge flows, our major contribution is that we not only quantifying the relative role of organizational networks by controlling the effect of local knowledge flows, but more importantly find that both tacit and codified knowledge can be transferred by long spatial distance via the organizational network of high-tech manufacturing cities. Since our empirical model is based on new product output of two high-tech sectors in a static scenario, results and conclusions may be somewhat different when applying to other types of interactions.

The third aspect stemmed from the critical evaluation of the first two. On the one hand, it was recognized that the concept of city network and its underpinnings could be determined by the behavioral logic of firms when specialization and networking play important economic roles. On the other hand, when it comes the externalities of organizational network on knowledge diffusion among cities, it suggests that industries respond differently and knowledge diffusion follows rather diverse spatial pathways through organizational networking, which depends on the core properties of pertinent knowledge and of the process of knowledge creation. Previous research on technological relatedness suggests that regions or countries could break technological trajectories and jump ahead by investing in building up external linkages (such as organizational network) and in their own innovation ability. What is left, then, is what lead us into considering the primary investment to build in knowledge based economy for a region beyond the dependence on network externalities.

The determinants of location choice of large high-skilled companies may convey us some concept on how a region could thrive while trying to survive in the modern networked economy. In knowledge-based economy, multinational corporations present several inconsistencies with the traditional theories that address cost minimization. Talent or human capital plays an increasingly significant role in orienting location choices of large corporations. In other words, knowledge-intensive firms will bear on relative higher costs in order to benefit from the source of human capital. It has been argued that there is a need to build a new paradigm of such changing geography of large and knowledge-based firms in a post-industrial economy.

In order to advance the new location choice theory and test our hypothesis, we applied the mixed discrete choice model to estimate the relative importance of human capital, agglomeration effects, and other traditional factors in the literature of location decisions using the data from five economic regions in China. Moreover, we examined the interaction of economic institutions and cultural distance in shaping the location choices of high-tech MNC firms when considering the role of human capital. According to the location choices of 1,526 high-tech MNC units in five economic regions in year 2008, our analysis confirmed the initial idea that knowledge-based MNCs show a strong tendency of locating their high-tech manufacturing firms in the place with great access to talent or human capital. Human capital has revealed its greater impact over industrial localization on the location of high skilled large corporations. Besides, economic institutions and its interaction with cultural distance also matters. Our theoretical conjecture is mainly built upon knowledge-based large corporations in the post-industrial era. As a result, neglecting these assumptions may lead to a misspecification of location choice theory. For the new paradigm of location choice theory, extra effort is required using longitudinal data to investigate the spatio-temporal evolution.

Following this path, although the theory of networking or relational thinking in economic geography has been popular for decades, with the slow change from hierarchical to horizontal in urban systems and the dominance of profit maximization in market economy, the concept of city network in general and the advantages of network externalities still have a long way to flourish as it is described in theoretical conjectures. There is a need for innovations in organizations and policy to fulfill the transformation of networking paradigm. More importantly, there is value in having more theoretical thinking depending on the methodological progress to enhance the conceptualization in the space economy. Finally, we suggest that access to human capital or talent along with decent institutional environment is the key for a region to conquer the realistic dilemmas and lead to a sustainable development in knowledge economy.

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