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**Do Capabilities Reside in Firms or in Regions?**
**Analysis of Related Diversification in Chinese Knowledge Production**

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**Abstract**

Do capabilities reside in firms, in regions, or in both? Most models of related diversification, building on the early work of Hidalgo et al. (2007), examine how the structure of economic activity within a region conditions the trajectory of diversification. Inter-regional flows are sometimes added to these models. The logic here is that capabilities are largely built-up within regions and sometimes shared between them. We challenge that logic, exploring whether capabilities are more likely to be built within the firm and to flow across spatial boundaries than they are to be built within the region flowing across firm boundaries. Analysis focuses on Chinese patent data spanning 286 cities over the period 1991 to 2015. We develop standard models of related diversification before examining how the branches of multi-locational firms diversify their knowledge portfolios. Evidence shows that the knowledge structure of firms is more important than the knowledge structure of regions in shaping branch diversification. We show that the influence of the firm and the region on diversification vary significantly between headquarters (HQ) branches and non-HQ branches of firms, and between the non-HQ branches of firms that are located in core and peripheral cities of China.

Keywords: Related diversification; Patents; Capabilities; China

## 1. Introduction

Since the pioneering work of Penrose (1959) and Cyert and March (1963), firm heterogeneity has been a cornerstone of attempts to understand competitive advantage. According to the resource-based view, the development and protection of firm-specific assets underpins the heterogeneity that fuels competition (Wernerfelt, 1984; Rumelt, 1984; Barney, 1991). Prahalad and Hamel (1990) build their resource-based model of firm performance around firm competence and capabilities. Kogut and Zander (1992) and Grant (1996) extend this work into the realm of technology. These arguments are put in motion by Teece et al. (1994; 1997) who explore the dynamics of capabilities, extending the evolutionary claims of Nelson and Winter (1982) in processes of search and creative destruction powered by competition. The path dependent nature of learning and the gradual accumulation of capabilities places diversification at the center of these dynamics.

Diversification may be understood as the entry of a firm into new types of activity (Ramanujam and Varadarajan (1989). That activity might focus on new product lines, new markets, new technologies or new forms of organization. Following Penrose (1959), as firms learn to use their resources more efficiently, they build up excess capacity and exploit possibilities that are not too distant from their core capabilities. In terms of technology, the local nature of search is well-known (Atkinson and Stiglitz, 1969; Stuart and Podolny, 1996) and, for many, represents the recombination of existing technological competence with new ideas that are sourced from a technology landscape that is complex and not well-mapped (Fleming and Sorenson, 2001). Over time, parts of the technology landscape become less of a terra incognita as knowledge complementarities become more well-known supporting forms of technological “lock-in” and related trajectories of technological diversification (Dosi, 1982; Breschi et al., 2003; Leten et al., 2007). However, processes of creative destruction continually rewire links within knowledge space such that related diversification might always be considered as emergent (see Kogler et al., 2017).

Within economic geography and related fields, considerable attention has focused on the related diversification of multi-locational firms and of the countries and regions in which they are active (Pavitt et al., 1989; Cantwell and Piscitello, 2000; Cantwell and Iammarino, 2001). The recent interest in regional diversification may be traced to the product space research of Hidalgo et al. (2007) and to the work of Boschma and Frenken on regional branching (2007). Key to these works is the finding that regions do not diversify along random growth paths, rather they accumulate capabilities that are related to their existing know how (Boschma and Iammarino, 2009; Neffke et al., 2011; Boschma et al., 2013; Balland et al., 2015) and to the knowledge sets of neighboring regions with whom they interact more intensively (Rigby, 2015). The focus on the region in much of this literature suggests, at least implicitly, that capabilities are territorially embedded and shared by the economic agents that comprise the regional economy. Yet, is this the case? We know that technology is highly proprietary and closely guarded by the firm? Where then do technological capabilities reside?

The primary research question that this paper engages is whether the capabilities that influence related technological diversification within multi-locational firms are located within the regions in which the firm's branches are located, or whether they are located within the firm. In the former case, the assumption is that capabilities are locked in regions and move across the boundaries of firms within each region, while the latter case suggests that capabilities are held by the firm and move across space within the boundaries of the multi-locational business unit. This research adds value to the related diversification literature in a number of ways. First, it extends the work of Lo Turco and Maggioni (2016) who examine firm and local relatedness in product diversification in Turkey over a short time period by focusing on technological diversification in Chinese cities over twenty-five years. Second, the paper contributes to the "agents of change" claims of Neffke et al. (2018) and Elekes et al. (2019) within another developing country context, using quite different data. Third, to the best of our knowledge, this is the first research to examine related technological diversification across Chinese cities, and certainly the first to separate the influence of different forms of relatedness density on diversification using patent data.

The core of the research examines how related technological diversification in the city-level branches of multi-locational Chinese firms is influenced by existing relatedness density within the branch, within the firm of which the branch is a part, and within the city (outside the firm) in which the branch is located. Our results show that the relatedness density of existing technological assets within the firm is many times more important than the relatedness density of the city's assets in predicting the path of new technology creation at the branch level. We go on to separate the headquarters (HQ) branches of multi-locational firms from non-HQ branches and show that the relative influence of firm and city relatedness vary significantly between branch types. Finally, we reveal significant differences in firm and local relatedness impacts on diversification in non-HQ establishments separated into core and peripheral cities in China. Overall, the results suggest that non-local, firm-specific capabilities play a much more important role in technological diversification than do purely local capabilities.

The rest of the paper is organized in three sections. In Section 2, a short review of the literature highlights the role of relatedness in recent thinking about diversification and discusses a number of extensions to early models of related diversification. In Section 3, we present our data and analysis. We move from an overview of sources, through some descriptive statistics by way of scene setting, to analysis of the standard model of regional related diversification and then to technological diversification within the branches of a sample of multi-locational firms. Section 4 provides a brief conclusion, summarizing the main findings and their implications for potential future research.

## 2. Literature Review

Territorial economies comprise assemblages of economic agents, institutions and resources of various kinds that are interconnected with such assemblages elsewhere. Capitalist competition, worker struggle and political pressures emanating from environmental and other concerns drive continuous change in these assemblages in terms of the mix of products supplied and the technologies used to produce them, in firm organization, inter-firm linkages and institutional forms that operate across multiple spatial scales (Schumpeter, 1939; Tushman and Anderson, 1986). Many of these changes are non-random, they evolve out of existing sets of capabilities, some local and some not, that reflect longer-running trajectories of competition and past choices by boundedly rational economic agents (Rigby and Essletzbichler, 1997). Sets of capabilities typically evolve relative slowly, though in times of crisis economic adjustment can be abrupt and painful as firms and regions are forced to reinvent themselves, raising important questions about resilience (Freeman and Perez, 1988; Christensen, 1997; Geels, 2002; Simmie and Martin, 2010). For the most part, market forces select the products that are favored and so direct more aggregate patterns of technological change, firm and regional fortunes (Nelson and Winter, 1982).

The diversification of regional economies is examined as a branching process by Frenken and Boschma (2007), in which new activities draw on and recombine related local assets. Klepper (2007) privileges the role of the firm in providing such assets, while Saxenian (1996) and Storper (1995) look to particular constellations of local institutions. The broad literature on agglomeration, clusters and learning regions places more weight on the importance of place-based factors, including the mix of economic agents and their interaction along with local social capital, in driving the pattern of regional economic development (Camagni, 1991; Glaeser et al., 1992; Lundvall, 1992; Maillat, 1995; Giuliani and Bell, 2005; Morgan, 2007). Others question the significance of the local asset base altogether (Bathelt et al., 2004; Fitjar and Rodriguez-Pose, 2017).

Quantitative analysis of regional diversification may be traced to Hidalgo et al. (2007) and their use of the concept of relatedness to explain how the export baskets of countries evolve as part of the process of development. Boschma et al. (2013) build on product-based measures of relatedness from export data to trace the emergence of new industries across Spanish regions. Neffke and Henning (2013) utilize a measure of industry relatedness based on overlapping product portfolios to explore the creation of new growth paths within Swedish regions. They show that growth paths linked to the existing industrial base of the region have a higher probability of occurring. Balland et al. (2015) build measures of relatedness between patent classes to explain patterns of technological diversification across US cities, to which Rigby (2015) adds geographical spillovers. Colombelli et al. (2014) follow a similar proximity-based approach to explain the emergence of nanotechnology in EU regions. Muneepeerakul et al. (2013) look at the dynamics of regional labor markets by building an occupational measure of relatedness, while Farinha et al. (2019) use a similar measure to examine the changing geography of jobs. Tanner (2016) provides some important correctives to the broader claims of much of this empirical work.

Regardless of the measure of relatedness used, most of the work just examined looks at capabilities as being embedded within regions. This gives rise to models of diversification where existing regional capabilities are the primary drivers of the direction of economic change. For Beugelsdijk (2007), such thinking raises concerns of an ecological fallacy. To be sure, the focus on regional aggregates reflects the difficulty of accessing firm-level data over space, yet much existing work on relatedness and diversification raises old questions about the relative importance of firm and regional characteristics in understanding the economic dynamics of regions (Markusen,1996; Sternberg and Arndt, 2001; Boschma, 2004).

In evolutionary economic geography, a number of papers have begun the process of unpacking regional economic diversification seeking to identify the "agents of change" (Neffke et al., 2018). Thus, Lo Turco and Maggioni (2016) investigate whether the addition of new products to a firm's product basket is influenced by local capabilities as well as by the firm's internal capabilities. They show, in the case of Turkey, that both local and firm capabilities play a significant, positive role in shaping product diversification after controlling for a number of firm characteristics. They go on to reveal that firm capabilities are much more important than local capabilities in directing new product development, especially in more peripheral eastern provinces of the country. In subsequent papers, Lo Turco and Maggioni (2019) and Elekes et al. (2019) look at the role of foreign multi-national enterprises (MNEs) versus local firms in shaping the path of regional economic diversification in emerging economies. They find that extra-regional flows of knowledge, transmitted via foreign MNEs, play the dominant role in local economic discovery. This extends the earlier work of Cantwell and Piscitello (2000) and Boschma and Iammarino (2009) on the significance of MNEs in transmitting knowledge over space.

Within the context of China, a number of authors have begun to outline patterns of diversification across firms and regions. In an early study, Zhao and Luo (2002) explore product diversification, the ownership structure and performance of foreign manufacturing subsidiaries operating in China. They report that related product diversification improves subsidiary performance over unrelated diversification. Lin and Wang (2008) show that regional industrial diversification is linked to latent patterns of comparative advantage. Using firm-level export data for the period 2000-06, Poncet and Waldemar (2013) use the measure of product relatedness from Hidalgo et al. (2007) to explore the relationship between the export performance of firms and patterns of comparative advantage at the city level. They reveal that firm-level exports grow faster for products that have higher relatedness density to the product spaces of cities from which exports originate. Wang et al. (2015) use Chinese patent data to study how the relationship between the volume of invention and technological diversification in China has evolved, after Archibugi and Pianta (1992) and Cantwell and Vertova (2004). This work is extended by Wang et al. (2016) who link technological diversification to the innovation capability of Chinese provinces. Using annual firm survey data, Guo and He (2017) report how industry relatedness has changed rapidly across different regions in China. They show that related diversification characterizes the evolution of industry space in coastal regions, while more unrelated forms of diversification are found elsewhere. Using city-level export data, Zhu et al. (2017) push this work a little further, revealing that extra-regional linkages, internal innovation and state policy have allowed some Chinese regions to engage in new path creation and evolve more rapidly than others. Zhou et al. (2019) use the same export data in an attempt to separate region and firm effects on related diversification. However, they assume that each establishment in their data represents a unique firm and thus they do not capture a firm effect that links diversification within plants that are part of a multi-locational firm.

There is considerable work left to do on related diversification at the sub-national level, especially in China. To date, there has been no analysis of technological diversification across Chinese cities using patent data. Patent data are useful insofar as they offer the researcher relatedness measures that are much easier to understand in terms of knowledge-based or cognitive proximity than the co-occurrence measures of Hidalgo et al. (2007). Indeed, it remains unclear to many, precisely what co-occurrence is actually measuring (Essletzbichler, 2015). Furthermore, we still do not know whether diversification in individual business establishments is driven more by region effects or by firm effects. In this regard, it is important to separate relatedness at the branch, firm and region levels. This is the direction we take in the analysis below. The other advantage of the patent data over exports and industry data is the availability of a much longer time-series.

## 3. Data and Analysis

This section of the paper comprises three sub-sections. The first sub-section outlines our primary data source and presents some basic descriptive statistics. The second sub-section examines a standard model of related diversification, after Hidalgo et al. (2007), that links the development of new technology classes within Chinese cities to the relatedness density of their existing patent stocks. This simple model is extended by incorporating technology spillovers of different kinds from neighboring cities. The third sub-section extends the literature on place-based capabilities to consider the influence of relatedness density at the branch-, firm- and city-level on diversification within the (city-based) branches of multi-locational firms.

### 3.1 Sources of Data and Descriptive Statistics

Exploration of the structure of knowledge in Chinese cities makes use of domestic "invention" patents filed with the Chinese Intellectual Patent Office (SIPO). To the best of our knowledge, this is the first paper to examine technological diversification in Chinese cities using patent data. Patents have become the standard means of tracking knowledge production and the pattern of technological diversification at the sub-national level, largely because of their availability and the wealth of information they contain (Feldman and Kogler 2010). However, it should be remembered that not all new knowledge is patented and that patent statistics themselves are somewhat biased indicators of invention, as pointed out by Pavitt (1985) and Griliches (1990).

We use the filing (application) date on SIPO patents to mark the timing of invention. The nature of the knowledge produced is characterized by the International Patent Classification (IPC) codes that are listed on each patent. The geography of Chinese patents is indicated by the location of the patent assignee(s). Patents with multiple assignees are fractionally split between the cities where those assignees are located. Note that multi-locational firms do not register all their patents at a single headquarters location. We exploit this fact in our analysis. The period of investigation runs from 1991 to 2015 and focuses on 5-year time steps. The patents examined are all granted. We stop analysis in 2015 because of right censoring in the data that occurs because of the time-lag between filing a patent and its grant date.

Table 1 reports the growth of knowledge production in China since 1991, disaggregated into seven major classes after Schmoch (1999). The IPC itself distributes patents across eight main classes, but that classification is not as useful in terms of separating key intellectual claims by broad sector of application. Taking the 20 years between the mid-point of our first time period (1991-95) and the mid-point of our last time period (2011-15), the number of inventor patents in China expanded at an annual average compound growth rate of 23.9%. That is an astonishing rate of increase. Most gains have occurred since 2000, so the recent growth in knowledge production within China is remarkable. That growth is relatively evenly balanced across the seven main classes reported in Table 1, with drugs and pharma recording the lowest annual average compound rate of growth at 19.6% and the electronics sector experiencing the most rapid growth at close to 30% per year on average between the early 1990s and 2015.

**Table 1: Aggregate patent numbers over three time periods**

| Aggregate Patent Class | 1991-95 | 2001-15 | 2011-15 | Annual Rate of Growth |
|---|---|---|---|---|
| **Electronics** | 3723.6 | 53056.8 | 685869.2 | 0.298 |
| **Computers & Communications** | 4304.7 | 22738.4 | 367063.5 | 0.249 |
| **Chemicals** | 8935.6 | 40033.7 | 425544.2 | 0.213 |
| **Drugs & Pharma** | 9775.2 | 47591.6 | 351120.3 | 0.196 |
| **Industrial Process** | 4396.7 | 24751.7 | 417003.6 | 0.256 |
| **Machinery & Transport** | 6226.3 | 34064.9 | 506056.0 | 0.246 |
| **Miscellaneous** | 2142.4 | 9286.1 | 141820.9 | 0.233 |
| **Total** | 39504.5 | 231523.2 | 2894477.7 | 0.239 |

Although different classes of patents have grown relatively evenly in the past 30 years, the spatial structure of invention changed a great deal. Table 2 and Figure 1 reveal the changing geography of Chinese invention since 1991 (see also Sun, 2000). The geography of knowledge production in China, at least as measured by patents, has remained relatively concentrated, though it has moved southwards. In 1991 to 1995, guided by the national economic development strategy, resource-based cities, such as the old industrial bases in the Northeast and the Bohai Rim registered relatively high numbers of patents. Some provincial capitals or regional central cities, such as Chengdu, Chongqing, Zhengzhou, Xi'an, Wuhan, Changsha, and Lanzhou, also captured a high share of patent production. In the most recent period (2011-2015), invention in China is mainly distributed in the eastern coastal areas, reflecting their diversified industrial structure and abundant human capital. The Beijing-Tianjin area with Beijing as the center, the Yangtze River Delta with Shanghai as the center, and the Pearl River Delta with Shenzhen as the center have become key nodes of invention.

**Table 2: Top 10 sites of invention in China**

| Rank | 1991-1995 | | 2001-2005 | | 2011-2015 | |
|---|---|---|---|---|---|---|
| 1 | Beijing | 6,028 | Beijing | 36,153 | Beijing | 291,512 |
| 2 | Shanghai | 1,681 | Shanghai | 29,077 | Shanghai | 187,058 |
| 3 | Shenyang | 1,296 | Shenzhen | 21,082 | Shenzhen | 156,914 |
| 4 | Tianjin | 1,190 | Tianjin | 14,041 | Suzhou(Jiangsu) | 118,091 |
| 5 | Chengdu | 1,050 | Hangzhou | 7,708 | Qingdao | 90,026 |
| 6 | Nanjing | 960 | Changsha | 6,599 | Nanjing | 84,071 |
| 7 | Xian | 893 | Guangzhou | 6,155 | Tianjin | 83,523 |
| 8 | Wuhan | 879 | Nanjing | 5,770 | Chengdu | 74,821 |
| 9 | Guangzhou | 798 | Wuhan | 4,909 | Changzhou | 72,974 |
| 10 | Dalian | 755 | Chengdu | 4,895 | Wuxi | 70,255 |

**Figure 1: Patent distribution in Chinese cities, 1991-95 and 2011-15**

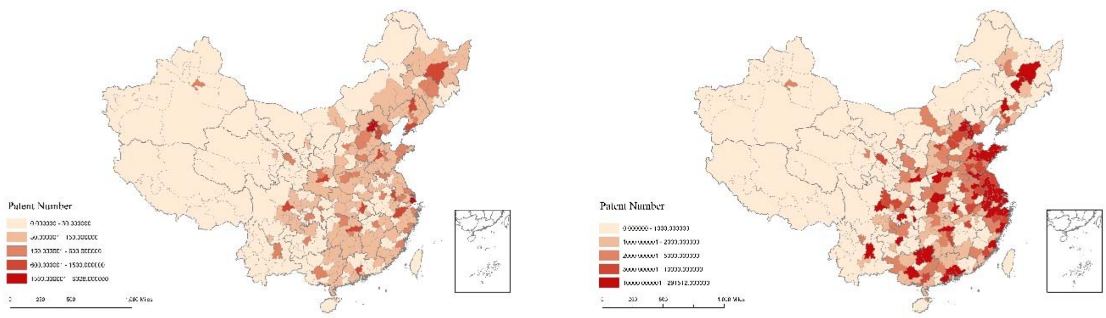
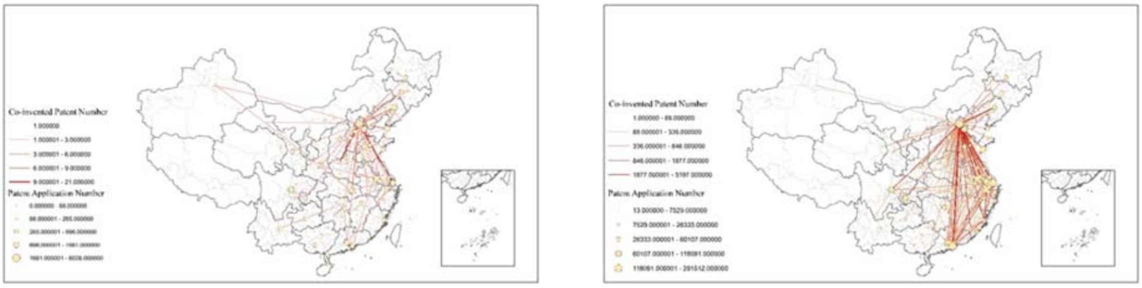



Figure 2 highlights patterns of collaboration in knowledge production between assignees located in different Chinese cities in 1991-95 and 2011-15. The ties between each pair of cities reflect the overall number of patent collaborations that link them. The darker the color of the ties, the more cooperation between economic agents within each pair of cities. It is clear from Figure 2 that the Chinese city collaboration network has changed markedly since the early-1990s. In the early period, the inventor collaboration network was dominated by a single central city, Beijing. Today, the collaboration network is polycentric, focused on Beijing, Shanghai, Shenzhen and Chengdu. While inter-city collaborations are dominated by these four cities, it is interesting to note that economic actors in Shanghai and Shenzhen engage in considerable collaboration with regional partners, much more so in fact than agents in Beijing and Chengdu. This may reflect regional policy and industrial structure.

**Figure 2: Collaborative structure of Chinese urban invention, 1991-95 and 2011-15**



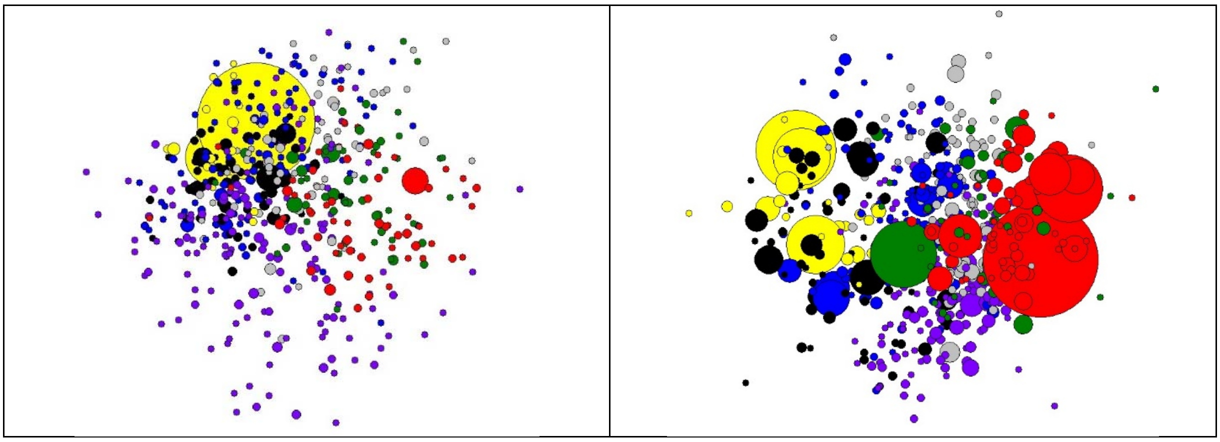
Investigation of technological diversification within Chinese cities requires construction of a Chinese knowledge space that represents the distance between IPC technology classes as recorded on domestic Chinese patent records. Co-class data gathered from individual patents are used to measure the proximity between all pairs of the 629 IPC classes listed on the SIPO data since 1991. This technique follows the earlier work of Jaffe (1986), Engelsman and van Raan (1994) and Kogler et al. (2013). To measure the proximity, or knowledge relatedness, between patent technology classes we employ the following method. Let $P$ indicate the total number of patent applications in the given sub-period. Then, let $F_{ip} = 1$ if patent record $p$ lists the classification code $i$, otherwise $F_{ip} = 0$. Note that $i$ represents one of the 629 primary technology classes into which the knowledge contained in patents is classified. In a sub-period, the total number of patents that list technology class $i$ is given by $N_i = \sum_p F_{ip}$. In similar fashion, the number of individual patents that list the pair of co-classes $i$ and $j$ is identified by the count $N_{ij} = \sum_p F_{ip}F_{jp}$. Repeating this co-class count for all pairs of IPC classes yields a symmetric technology class co-occurrence matrix $\boldsymbol{C}$ the elements of which are the co-class counts $N_{ij}$. The co-class counts are converted into measures of proximity through division by the square root of the product of the number of patents in each of the two classes, or

$$S_{ij} = {N_{ij}}\Big/{\sqrt{N_i * N_j}}$$

where $S_{ij}$ is an element of the standardized co-occurrence matrix ($\boldsymbol{S}$) that indicates the technological proximity, or knowledge relatedness, between all pairs of patent classes in a given period. The elements on the principal diagonal of $\boldsymbol{S}$ are set to 1. An $S_{ij}$ value of zero would indicate that there are no patents in a given period that contain class codes $i$ and $j$.

The network of technological relatedness across the 629 IPC patent class nodes is mapped with the aid of UCINET (Borgatti et al., 2002). The visualizations of the Chinese knowledge space in Figure 3 are generated with the Gower-scaling metric (Gower, 1971). The node colors in the figure represent the seven aggregate technology groups identified earlier within the IPC. Node size indicates the number of patents granted within a class. In 1991-95 the largest node is (A61K = preparations for medical, dental or toilet purposes) with 5,289 patents. In 2011-15, the largest node (G06F = electric digital data processing) contains 133,275 patents. Figure 3 shows that technology classes cluster within their more aggregate (color) groupings. The clustering or proximity of technology nodes indicates that they share a common knowledge base. The closer the nodes, the higher the relatedness between them and the greater the cognitive overlap. The electronics cluster is clear in Figure 3 for the period 2011-15. The links between the chemicals classes (black) and the drugs and pharma (yellow) technologies is also apparent. Figure 3 also make clear the relatively rapid shift in the nature of Chinese invention.

**Figure 3: Chinese knowledge space, 1991-95 and 2011-15**



Notes: Red = Electronics (1), Green = Computers & Communications (2), Chemicals = Black (3), Yellow=Drugs & Pharma (4), Blue = Industrial Process (5), Purple = Machinery & Transport (6), Grey = Miscellaneous (7)

Table 3 reports the average relatedness density for the seven aggregate technology classes of the IPC. The relatedness density values are averaged (unweighted) across the 286 Chinese cities that we investigate. The relatedness density of technology class $i$ in city $c$ at time $t$ is calculated as

$$Relatedness\ Density_{ict} = \frac{\sum_{j \neq i} S_{ijt} * RTA_{cjt}}{\sum_{j \neq i} S_{ijt}}$$

where $RTA_{cj}$ is a binary (0/1) variable representing regional technological advantage. RTA takes the value 1 when the city share of patents in class $j$ exceeds the share of a reference region, typically the sum of geographical units examined. In this case, the reference region comprises the 286 Chinese cities examined. These cities accounted for 99.8% of all Chinese patents granted over the period 2011-15. The relatedness density values range from 0 to 1, with 0 indicating that a city does not have RTA in any of the technology classes $j$ that are related to class $i$. As the relatedness density index approaches 1, then cities have RTA in knowledge stocks $j$ that are increasingly strongly related to technology in class $i$. In other words, relatedness density reflects the potential of a region to develop new technologies based on existing capabilities (Balland et al., 2019).

Table 3 indicates that the relatedness density in each aggregate technology class has increased on average within Chinese cities over the last thirty years or so. This means that Chinese cities are increasingly specializing in terms of invention (see also Honggang et al., 2019). Among the seven aggregate patent categories, the relatedness density of Drugs and Pharma is the highest in 2011-15, indicating that invention within this technology grouping is the most likely to occur in cities with a strong knowledge core in the same category. Relatedness density is lowest in China in the electronics sector in 2011-15. Inventive specialization across Chinese cities has grown fastest in the Machinery and Transport classes of the IPC and the least rapidly in Drugs and Pharma classes.

**Table 3: Average relatedness density by technology type across cities**

| Aggregate Patent Class | 1991-95 | 2001-15 | 2011-15 | Annual Rate of Growth |
|---|---|---|---|---|
| **Electronics** | 0.0891 | 0.1246 | 0.1844 | 0.037 |
| **Computers & Communications** | 0.1018 | 0.1376 | 0.2075 | 0.036 |
| **Chemicals** | 0.1639 | 0.2104 | 0.3304 | 0.036 |
| **Drugs & Pharma** | 0.2106 | 0.3523 | 0.3947 | 0.032 |
| **Industrial Process** | 0.1106 | 0.1789 | 0.2905 | 0.049 |
| **Machinery & Transport** | 0.0922 | 0.1544 | 0.2891 | 0.059 |
| **Miscellaneous** | 0.1139 | 0.1686 | 0.2617 | 0.042 |

### 3.2 A Model of Related Diversification

The standard model of related diversification imagines that cities (or regions and countries) will diversify into those technology classes that are related to their existing technological base. The logic underpinning this model is that the economic agents that comprise an urban economy build sets of capabilities over time that allow them to produce distinct types of technological knowledge. The path dependent nature of capability development means that cities and regions develop industrial and technological repertoires that are not rapidly changed (Grabher, 1993; Rigby and Essletzbichler, 1997). Thus, over time, they tend to accumulate new sets of capabilities that are closely connected to their existing knowledge cores.

We track technological diversification by tracing measures of revealed technological advantage (RTA) for all technology classes within cities from one time-period to the next. RTA is typically expressed as a (0/1) binary variable that takes the value one when the city share of patents in a class exceeds the share of a reference region, typically the sum of geographical units examined. In this case, the reference region comprises the 286 Chinese cities in our data frame. When an RTA value switches from zero to one, then a city has successfully diversified into a new technology. Cities can lose capabilities over time, though the focus here is on technological entry. We test the impact of relatedness density on technological diversification with a fixed effects regression model that takes the following form

$$RTA_{ict} = \beta_0 + \beta_1 Density_{ict-1} + \boldsymbol{\beta_k X_{kcit-1}} + \gamma_c + \gamma_t + \varepsilon_{ict} \qquad (1)$$

In equation (1), the dependent variable indicates RTA in city *c*, technology class *i* at time *t*. Equation (1) models the probability of a city developing RTA as a function of the relatedness density of a technology class to the existing knowledge base of the city recorded at time *t-1*. The relatedness density of technology class *i* in city *c* at time *t* is calculated as

$$Relatedness\ Density_{ict} = \frac{\sum_{j \neq i} S_{ijt} * RTA_{cjt}}{\sum_{j \neq i} S_{ijt}}$$

The relatedness density values range from 0 to 1, with 0 indicating that a city does not have RTA in any of the technology classes *j* that are related to class *i*. As the relatedness density index approaches 1, then cities have RTA in knowledge stocks *j* that are increasingly strongly related to technology in class *i*. In other words, relatedness density reflects the potential of a region to develop new technologies based on existing capabilities (Balland et al., 2019).

Theory suggests that the density variable should be positively related to the change in RTA. The term $\boldsymbol{\beta X}$ in equation (1) represents a series of city control variables. We include city-size as measured by the number of patents produced, a measure of technological specialization in the city captured in a technology class Herfindahl, and a measure of competition over technological rents proxied by the number of firms and other organizations that patent in a city divided by the number of patents. Note that the correlation between the city's patent sum and the competition measure is r = -0.12. We would expect competition to increase the probability of RTA as diversification is a key competitive strategy. In similar fashion, we would hypothesize that the Herfindahl exhibit a negative relationship with RTA, as more specialized cities would tend to have RTA in fewer classes than less specialized cities. Larger cities tend to be more diverse and so city-size might be expected to raise the probability of entry.

Results from estimating slightly different variants of the model in equation (1) are reported in Table 4. The logit model is used because of the binary dependent variable. Model 1 is surely mis-specified as it includes only relatedness density as an independent variable. This model is incorporated as a baseline in order to explore changes in the relatedness density coefficient with the addition of various controls. As hypothesized, the lagged value of relatedness density is a positive and significant predictor of technological diversification at the city level. The coefficient in the model represents the impact of a unit-change in relatedness density on the log odds of the probability of RTA being established in a technological class. Further interpretation of the logit is given below.

Model 2 incorporates city level covariates. The Herfindahl operates as expected, with increases in the technological specialization of cities dampening the probability of diversification. The sign on the competition variable is also positive, as expected, though this variable is not significant. Note that if we do not cluster standard errors at the city-level, the competition variable is significant at the 0.01 level. The city-size variable (patent sum) has a coefficient that is negative and significant, counter to expectations. Thus, diversification appears to slow down as cities expand in terms of the number of overall patents they generate. Model 3 adds spatial lags to the analysis. Coordinates for our 286 Chinese cities were used to generate an inverse distance spatial weights matrix. The product of this matrix and the entire city-technology density matrix provides a measure of the impact of relatedness density in neighboring cities on diversification within a target city. A positive coefficient would suggest that neighbors with knowledge stocks that are closely related to a particular technology class would not inhibit a specific city from diversifying into that same class. A positive coefficient might indicate some degree of knowledge-sharing between neighboring cities rather than competition. The coefficient on the geographical spillover variable in Model 3 is positive and significant. Model 4 offers a more refined variant of the spatial lag, incorporating direct evidence from patent data on inter-city collaboration. For each 5-year period examined, we find the total number of inter-city collaborations by technology class reported in the patent records. The product of this collaboration matrix and the city-technology density matrix yields the geography of collaboration variable. The coefficient on this variable is also positive and significant, though not quite as strong as the spillover effect. Across all these models, relatedness density has a similar and large influence on the probability of technological diversification within the city. This result matches those typically reported for technological diversification across industrialized economies (Boschma, 2015; Rigby, 2015).

**Table 4: Logit regressions of related diversification**

| | Dependent Variable: City RTA (1991-2015) | | | |
|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 3** | **Model 4** |
| **Lag relatedness density** | 1.5841***<br>(0.0308) | 1.5428***<br>(0.0297) | 1.0648***<br>(0.1152) | 1.5388***<br>(0.0296) |
| **Lag city patent sum** | | -0.0000***<br>(0.0000) | -0.0000***<br>(0.0000) | -0.0000***<br>(0.0000) |
| **Lag city Herfindahl** | | -2.0268***<br>(0.6226) | -2.2126***<br>(0.6564) | -2.0037***<br>(0.6204) |
| **Lag technology competition** | | 0.0672<br>(0.0442) | 0.0449<br>(0.0460) | 0.0653<br>(0.0439) |
| **Lag geography spillover** | | | 0.0611***<br>(0.153) | |
| **Lag geography collaboration** | | | | 0.0005*<br>(0.0003) |
| **Constant** | -2.2703***<br>(0.0206) | -2.1410***<br>(0.0296) | -2.6526***<br>(0.1362) | -2.1417***<br>(0.0294) |
| **Time fixed effects** | Yes | Yes | Yes | Yes |
| **City fixed effects** | Yes | Yes | Yes | Yes |
| **Observations** | 628,685 | 627,427 | 627,427 | 627,427 |

Notes: All models were run with robust standard errors clustered at the city level. * significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

All the models discussed in Table 4 include time and city fixed effects and they incorporate robust standard errors clustered at the city level. This is the appropriate form of the related diversification model. By including city fixed effects, we are averaging the impacts of relatedness density on diversification across Chinese cities, while controlling for city-specific factors that may influence levels of diversification. The coefficients in the model are log odds ratios that report how a one-unit change in an independent variable influences the logarithm of the probability of technological diversification divided by the probability of no technological diversification. The log odds ratios for the relatedness density variables are mostly around the value 1.5. This value implies that a unit change in relatedness density would increase the probability of technological diversification by about 82%. Of course a one unit change in relatedness density is unlikely with such values constrained to the range of 0 to 1. Using the margins command in STATA, evaluated with independent variables at their means, a change of one standard deviation in relatedness density would increase the average probability of diversification by about 5%.

Time fixed effects, that are common across cities, control for temporal shocks to the diversification process. Note that we get broadly similar results on key variables using the linear probability model. We also get a positive and significant coefficient on relatedness density if we set the model up in panel form where the units of observation are technology classes within cities. However, in panel form the focus of the model is on how changes in relatedness density within a city-technology class pair influences entry. This model does not capture as well how individual cities diversify across technology classes.

### 3.3 Related Diversification within Multi-Locational Firms: Do Capabilities Reside in Firms or Regions?

The standard model of related diversification is typically operationalized with units of observation that are spatial - countries, cities or regions. In large part, this reflects the availability of geographical information and the difficulty of assembling firm-level data. Development of the model over spatial units pushes the researcher to assume, at least implicitly, that the capabilities that really count are located within regions, though they may sometimes flow between them as the analysis above indicates. For the most part, then, capabilities are seen as residing in locations rather than in firms, moving across firm boundaries within regions more readily than they move within firms across space. However, there are strong reasons to doubt this assumption, especially when dealing with technologies that tend to be highly proprietary. In this sub-section of the paper, we explore whether evidence supports the notion that capabilities are located within firms or within regions.

Of course, if capabilities reside in firms, then it might be said that certain capabilities are also located in the regions where specific firms operate. Still, we must be careful on this issue because a great deal of analysis within economic geography assumes that the co-location of economic agents implies some sharing of capabilities and the emergence of place-specific assets and relationships that fuel regional performance. While it is undoubtedly the case that place-specific assets of tangible and intangible kinds do emerge within economic clusters (Storper, 1995; Baldwin et al. 2008), the impacts of these assets are heterogeneous (Neffke, 2009; Potter and Watts, 2011; Rigby and Brown, 2015) and not broadly quantified. In the analysis below, we separate the influence of firm-specific and city-specific forms of relatedness density on technological diversification.

Investigation focuses upon a sub-sample of Chinese patents that are connected to multi-locational firms. These are firms that have branches in different Chinese cities and that patent in each of those cities. The multi-locational firms were identified with firm data from Bureau van Dijk (BVD). Because of the time-intensive nature of identification, our analysis focuses only on the largest 200 multi-locational firms operating across Chinese cities. These firms are responsible for generating around 700,000 patents between 1991 and 2015, some 20% of the Chinese total. On average, each of these multi-locational firms has a branch in five different Chinese cities. The largest firm, State Grid Corporation of China, had 67 branches that generated patents across Chinese cities in the most recent period examined.

In order to explore the location of capabilities, we set up another related diversification model, this one focused on the activities of the branches of multi-locational firms. For each branch we note those technologies (IPC classes) in which the branch attained RTA across our five-year time windows. Measures of relatedness density are then built for all observations at the branch, firm and city level. Note that we start with a reference dataset that includes only the patent data within the multi-locational firms that we examine. This reference set provides the denominator in the RTA calculations. We use different data for robustness checks on our analysis as discussed later. The multi-locational firm data includes patent information from all the branches that belong to the firm (through ownership). Subsidiaries and joint ventures are not included with these data.

Somewhat more formally, our dependent variable, RTA, is now defined at the level of a branch as

$$RTA_{branch\ i} = \frac{Patents_{ifc} / \sum_c Patents_{ifc}}{\sum_c \sum_f Patents_{ifc} / \sum_i \sum_f \sum_c Patents_{ifc}}$$

where $i$ refers to the technology (IPC patent) class, $f$ to the firm and $c$ to the city. Note again that the overall denominator here is the class share in the reference region (the sum of all branches across cities in China that are owned by the 200 firms that we examined). RTA at the firm level (part of the relatedness density variable defined at the firm level) is defined as

$$RTA_{firm\ i} = \frac{\sum_c Patents_{ifc} \,/ \sum_i \sum_c Patents_{ifc}}{\sum_c \sum_f Patents_{ifc} / \sum_i \sum_f \sum_c Patents_{ifc}}$$

where the overall denominator is the same as in the RTA for the branch. Finally, RTA at the city level is defined as

$$RTA_{city\ i} = \frac{\sum_f Patents_{ifc} \,/ \sum_i \sum_f Patents_{ifc}}{\sum_c \sum_f Patents_{ifc} / \sum_i \sum_f \sum_c Patents_{ifc}}$$

These different measures of RTA allow us to define three relatedness density terms in our model, one for the branch, firm and city:

$$Density_{branch,\ i} = (\sum_{j \neq i} S_{ij} * RTA_{branch}) / \sum_{j \neq i} S_{ij}$$

$$Density_{firm,\ i} = (\sum_{j \neq i} S_{ij} * RTA_{firm}) / \sum_{j \neq i} S_{ij}$$

$$Density_{city,\ i} = (\sum_{j \neq i} S_{ij} * RTA_{city}) / \sum_{j \neq i} S_{ij}$$

where $S_{ij}$ is the relatedness between classes *i* and *j* built from multi-locational firm data alone, and where RTA = 0/1. The new model to be estimated is

$$RTA_{branch,\ it} = \beta_{branch} Density_{branch,\ it-1} + \beta_{firm} Density_{firm,\ it-1} + \beta_{city} Density_{city,\ it-1} + FE_{time} + FE_{firm} + \varepsilon \qquad (2)$$

and where the terms should all be familiar at this time.

Results from estimating the relatedness density model at the branch level are shown in Table 5. Once again, we estimate a logit model of technological diversification with firm and time fixed effects. We add city fixed effects in Model 6. With only one HQ plant per firm in Model 7, city-level fixed effects are correlated with firm effects and thus dropped. To aid comparison between Model 7 and Model 8 we do not incorporate city fixed effects in the latter. Robust standard errors were clustered at the firm level throughout. As a robustness check we also constructed measures of relatedness using data generated from all Chinese patents rather than just those associated with our sample of multi-locational firms. The results reported here did not change.

Model 5 is the logit for all branches in our sample of multi-locational firms. The three coefficients on the different lagged measures of relatedness density, those observed within the branch, within the firm and within the city are positive and significant implying that existing knowledge assets at these three levels influence technological diversification within and across the branches of multi-locational firms. The coefficients represent the influence of a one-unit increase in the independent variables upon the log odds of RTA being developed within a technological sector in the branches of a multi-locational firm. Note that the coefficient on the relatedness density of the firm has the largest influence on technological diversification within a branch, that coefficient being 1.1 times greater than the coefficient on relatedness density within the branch and 2.0 times greater than the coefficient on relatedness density within the city. This result suggests that technological know-how is much more likely to flow across regions within the boundaries of the firm than it is to flow across firm boundaries within the city. Adding city fixed effects in Model 6 indicates that the firm density coefficient is almost 1.5 times larger than the branch coefficient and 3.5 times larger than the city density coefficient.

While Models 5 and 6 suggest that capabilities reside largely within the firm and its branch plants, they do not separate headquarters branches from non-HQ branches. The broader literature on multi-locational firms makes clear that the flows of information among their branches is asymmetric (Gupta and Govindarajan, 2000; Hansen, 2002). Audia et al. (2001) and Singh (2008) discuss the costs and potential gains from distributed innovation. If non-HQ branches are strategically located to tap into local knowledge resources, then city relatedness density should be relatively more important in these branches than in the HQ branches of firms. Firm relatedness density should be relatively more important in HQ branches as they are developing technologies that may originate in R&D activities across a series of non-HQ establishments. This is indeed what we see in Model 7. Here the model specification changes to include a dummy variable indicating whether the branch observations refer to non-HQ branches (0) or to HQ branches (1), and three interaction terms that are the product of the HQ dummy and each of our relatedness density measures. Thus, when the HQ dummy takes the value 0 we are examining non-HQ branches and the interaction terms drop out of the model. The constant term now represents the average log odds of related diversification with all density variables taking the value zero. For non-HQ establishments, the relatedness density log odds coefficients for the branch, the firm and the city all have quite similar magnitudes. However, note that the relative sizes of the density coefficients, especially those connected to the city effect, are much higher than in Models 5 and 6. As we shift to HQ branches, related density at the firm level is significantly greater than it is for non-HQ branches, and city relatedness density has a significantly smaller impact on diversification in HQ plants than in non-HQ plants. These results suggest that HQ branches are gathering and using more firm-level information in their own diversification process, while non-HQ branches look more toward local non-firm knowledge sharing than HQ branches, perhaps fulfilling a role as "local listening posts".

**Table 5: Related diversification in branch level data (firm fixed effects)**

| | Dependent Variable: Branch RTA (1991-2015) | | | |
|---|---|---|---|---|
| | **Model 5** | **Model 6** | **Model 7** | **Model 8** |
| **Lag Branch Density** | 1.6940***<br>(0.1099) | 1.4024***<br>(0.1099) | 1.8800*<br>(0.7370) | 0.9376*<br>(0.6206) |
| **Lag Firm Density** | 1.8806***<br>(0.1118) | 2.0426***<br>(0.1145) | 1.6671***<br>(0.1906) | 2.2961***<br>(0.1932) |
| **Lag City Density** | 0.9256***<br>(0.0674) | 0.5648***<br>(0.0504) | 1.4856***<br>(0.3423) | 1.6351***<br>(0.4354) |
| **Lag Interact-branch** | | | 0.0861<br>(0.3941) | 0.6862<br>(0.5079) |
| **Lag Interact-firm** | | | 0.5607***<br>(0.1803) | -0.0142<br>(0.1646) |
| **Lag Interact-city** | | | -0.7499**<br>(0.3538) | -0.9667**<br>(0.4326) |
| **Lag HQ Branch dummy** | | | 1.4954***<br>(0.1069) | |
| **Lag Core-Periphery dummy** | | | | 0.4920***<br>(0.1172) |
| **Constant** | -5.3318***<br>(0.0513) | -5.1966***<br>(0.5886) | -6.7827***<br>(0.1190) | -4.2213***<br>(0.0972) |
| **Time fixed effects** | Yes | Yes | Yes | Yes |
| **Firm fixed effects** | Yes | Yes | Yes | Yes |
| **City fixed effects** | No | Yes | No | No |
| **Observations** | 3,095,127 | 3,095,127 | 2,292,620 | 1,864,340 |

Notes: All models were run with robust standard errors clustered at the firm level. * significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

Model 8 focuses exclusively on non-HQ branches, exploring whether non-HQ establishments in core cities diversify in different ways than non-HQ establishments in peripheral cities. Core and peripheral cities were identified from networks of inter-city collaboration on individual patents, illustrated in Figure 2, using the "coreness" network algorithm of Borgatti and Everett (2000). Interaction effects are used again to reveal the significance of differences in relatedness density measures on diversification between non-HQ branches in core cities and in peripheral cities. In peripheral cities, diversification in non-HQ establishments is positively and significantly impacted by branch, firm and city relatedness density, though the relative size of the branch coefficient is much smaller than in the other models we have considered. So it looks like diversification in non-HQ branches in peripheral cities depends more on firm and city relatedness density. The coefficient on the city density variable is relatively large in Model 8, indicating that patterns of diversification in these non-HQ branches depend quite heavily on local knowledge assets outside the firm. This finding is consistent with Model 7. As we shift to non-HQ firms in core cities, the only relatedness density coefficient that changes significantly is that on city density. In core cities local knowledge assets play a significantly smaller role in diversification than they do in non-core cities. This is a surprising result that we did not expect.

The models in Table 5 are estimated with firm-level fixed effects. Because those fixed effects do not apply at the individual branch level, the results in Table 5 are based on both the within and between establishment variance within the individual firm. This model specification captures the way in which the firm might employ its different establishments to specialize in the production of distinct knowledge subsets. Of course, this note also raises the question of how the results change if we employ branch-level fixed effects. With branch fixed effects, the analysis shifts toward examination of the within branch variance only and a vision of the establishment as largely independent. It is unclear whether firm or branch fixed effects are most appropriate. The most disaggregate fixed effects are often preferred in the literature, but inefficiencies in estimating the within effects model at the branch level should not be ignored. For completeness, we report branch-level fixed effects models corresponding to Table 5 in the Appendix. Note that the results obtained from those models are somewhat different to those reported above. The dominance of firm relatedness density over city relatedness density remains, but plant relatedness density seems to work quite differently. The Appendix also reports results for the models of Table 5 generated from the linear probability model using firm fixed effects. In all estimation standard errors are clustered at the firm level.

## 4. Conclusion

In this paper we explored patterns of technological diversification within cities and within the branches of multi-locational firms in China. Our purpose was to better understand the process of knowledge sourcing. Much of the related diversification literature in evolutionary economic geography has focused on the region as a unit of analysis. Implicit within much of that work is the claim that the technological structure of the region is a key driver of the direction of diversification. While this argument might raise old questions about the spatial ecological fallacy and the reification of the region, the issue is surely more complex today as we recognize the co-evolution of firms and the regional economies of which they are a part. The mobility of workers between firms, the formal and informal relationships between firms and the institutional structures that are so much a part of the regional economy make it difficult at times to separate that which is created within the firm from that which is learned in the broader environments within which firms operate. Another way of saying this is that the knowledge structure of the region and that of the firms that comprise the region are endogenous. Matters are complicated further by the flow of knowledge between firms located in different regions and by the flow of knowledge within the multi-locational firm.

Still, it may be possible to disentangle the influence of the firm from the influence of the region in the process of technological diversification. At least, this was the task that we set for ourselves. To date, there has been relatively little analysis of the Chinese knowledge space and the evolution of technological relatedness between patent classes within China, an emerging economy that is now generating patents at a faster pace than the United States. We mapped the Chinese knowledge space in the periods 1991-95 and 2011-15, reporting how the relative distances between different technologies has shifted and showing those technology groupings that have experienced the fastest growth between the two periods just noted. Measures of technological relatedness, a key input to models of diversification, were generated for all 629 distinct technology classes of the IPC across 286 Chinese cities for five time-intervals since 1991. At the city-level, consistent with previous work on technological diversification, the knowledge stocks of cities are shown to be a reliable predictor of the pattern of future technological diversification. Inter-city flows of a generic spatial form and flows that capture inventor collaboration are also shown to exert a positive and significant influence on related diversification.

To separate the impacts of firms from regions on diversification, a sample of 200 multi-locational firms was produced. These firms were responsible for approximately 20% of all Chinese patents. The multi-locational firms have on average five branches located in different cities across China. Patents were recorded for each of these branches independently of the HQ branch of the firm. We examined patterns of technological diversification within these branches, generating separate measures of the effects of relatedness density to the lagged knowledge assets of the branch, to the parent firm and to the city in which the branch was located. Using fixed effects logit models, the influence of related density within the firm was always larger than the relatedness density of the city on diversification at the branch level. The logit coefficients on the firm and city density measures varied as much as a factor of 4 in some models. Interpreted somewhat differently, a one-unit increase in relatedness density at the firm-level increases the average probability of branch diversification by about 25 percentage points more than a one-unit increase in relatedness density at the city-level.

Building on the management literature that details asymmetries of information flow between the plants of multi-unit firms, the HQ and non-HQ branches of the firms in our sample were separated. There is significantly more diversification in HQ plants than non-HQ plants. The influence of relatedness density at the branch, the firm and the city levels on diversification within non-HQ branches were much closer to one another than in the overall model just discussed. Interactions reveal that these relatedness density measures change significantly as attention switches to HQ branches. Diversification in HQ units is significantly more impacted by relatedness density within the firm as a whole and significantly much less impacted by relatedness density in the city where they are located. These results suggest that non-HQ plants might be playing the role of "listening posts", gathering technological knowledge from outside the firm, while HQ plants are assimilating that knowledge to a greater degree than they are tapping local sources of non-firm technological intelligence.

Finally, separating non-HQ plants into core and peripheral cities in China, results reveal that branches in core cities have higher overall levels of diversification than those in peripheral locations. Perhaps as expected, branch diversification is much more dependent on firm and city effects in these non-HQ plants than on the knowledge assets of the branches themselves. Rather surprisingly, diversification in the non-HQ plants of core cities is significantly less impacted by city-related density than in peripheral cities.

In sum, we have added value to the "agents of change" literature that has focused on mining firm-level data to help understand the dynamics of diversification that occur within regions. We push that literature into the patent realm focusing on technological diversification at the level of the plant, the firm and the city within China. Our results suggest that there is a lot more heterogeneity in the diversification data than we have recognized to this point. Much more work is required to see if these patterns hold up in other settings and to unpack their meaning for our understanding of the evolution of relatedness and of firm and region dynamics. Understanding the process of diversification in single-plant firms also demands more attention.

**Appendix**

**Table A1: Table 5 re-estimated using the linear probability model (firm-level fixed effects)**

| | Dependent Variable: Branch RTA (1991-2015) | | | |
|---|---|---|---|---|
| | **Model 5** | **Model 6** | **Model 7** | **Model 8** |
| **Lag Branch Density** | 0.2406***<br>(0.0098) | 0.2357***<br>(0.0097) | 0.2229***<br>(0.0147) | 0.1902***<br>(0.0531) |
| **Lag Firm Density** | 0.0528***<br>(0.0064) | 0.0539***<br>(0.0063) | 0.0526***<br>(0.0062) | 0.0384***<br>(0.0070) |
| **Lag City Density** | 0.0179***<br>(0.0019) | 0.0145***<br>(0.0015) | 0.0118***<br>(0.0020) | 0.0182***<br>(0.0081) |
| **Lag Interact-branch** | | | -0.1138***<br>(0.0375) | 0.0289<br>(0.0495) |
| **Lag Interact-firm** | | | 0.1298***<br>(0.0311) | 0.0286***<br>(0.0069) |
| **Lag Interact-city** | | | 0.0142**<br>(0.0040) | -0.0082<br>(0.0081) |
| **Lag HQ Branch dummy** | | | 0.0146***<br>(0.0015) | |
| **Lag Core-Periphery dummy** | | | | 0.0017***<br>(0.0005) |
| **Constant** | 0.0003<br>(0.0005) | 0.0127<br>(0.0108) | 0.0002***<br>(0.0005) | -0.0011<br>(0.0008) |
| **Time fixed effects** | Yes | Yes | Yes | Yes |
| **Firm fixed effects** | Yes | Yes | Yes | Yes |
| **City fixed effects** | No | Yes | No | No |
| **Observations** | 3,095,127 | 3,095,127 | 3,095,127 | 2,301,426 |

Notes: All models were run with robust standard errors clustered at the firm level. * significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

**Table A2: Table 5 re-estimated using branch-level fixed effects (logit specification)**

| | Dependent Variable: Branch RTA (1991-2015) | | | |
|---|---|---|---|---|
| | **Model 5** | **Model 6** | **Model 7** | **Model 8** |
| **Lag Branch Density** | -0.5730***<br>(0.1247) | | -0.2140*<br>(0.1112) | -0.4338<br>(0.5061) |
| **Lag Firm Density** | 2.6858***<br>(0.1206) | | 2.7109***<br>(0.1232) | 2.7266***<br>(0.1324) |
| **Lag City Density** | 0.7705***<br>(0.0521) | | 0.7994***<br>(0.0573) | 0.9363***<br>(0.1987) |
| **Lag Interact-branch** | | | -0.4303*<br>(0.2597) | 0.4620<br>(0.4940) |
| **Lag Interact-firm** | | | -0.2738<br>(0.2283) | -0.0789<br>(0.1049) |
| **Lag Interact-city** | | | -0.0894<br>(0.1081) | -0.2457<br>(0.2101) |
| **Lag HQ Branch dummy** | | | -1.0433***<br>(0.0532) | |
| **Lag Core-Periphery dummy** | | | | -0.0518<br>(0.3060) |
| **Constant** | -6.7806***<br>(0.2712) | | -6.8519***<br>(0.0005) | -11.2250***<br>(0.3420) |
| **Time fixed effects** | Yes | | Yes | Yes |
| **Branch fixed effects** | Yes | | Yes | Yes |
| **Observations** | 3,095,127 | | 3,095,127 | 1,668,203 |

Notes: All models were run with robust standard errors clustered at the firm level. * significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level. Model 6 is not estimated as city fixed effects are collinear with branch fixed effects.

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