

# External linkages and regional diversification in China: The role of foreign multinational enterprises

EPA: Economy and Space

2024, Vol. 56(4) 1077–1101

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DOI: 10.1177/0308518X231223621

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## Abstract

This article investigates the role of local external linkages in supporting regional industry entry in new activities, by specifically considering the role of foreign multinational enterprises (MNEs). Theoretically, we construct an original conceptual framework encompassing different potential trajectories of regional diversification based on the presence of MNEs. Empirically, we focus on the case of 279 Chinese prefectures over 1998–2007 and our results suggest that the presence of MNEs is associated with industry entry in unrelated and complex industries, supporting the idea that regional external linkages can activate processes of diversification that modify the technological and industrial portfolio of local economies.

## Keywords

Multinational enterprises, relatedness, complexity, regional diversification, China

## Introduction

The argument that *relatedness* is a key driver of regional diversification has been at the core of recent studies in economic geography, especially those with an evolutionary approach (Boschma, 2017; Boschma et al., 2015, 2023; Gao et al., 2021; Hidalgo et al., 2007, 2018). The central tenet of this

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strand of literature is that regional diversification is a path-dependent process that heavily relies on the pre-existing productive structure and capabilities present in a region. The underlying explanation for this is that the resources and capabilities required to jump to unrelated industries or technologies are harder to acquire compared to those needed to enter related sectors. This insightful observation on the process of regional development is condensed into the idea of ‘related diversification’ and ‘the principle of relatedness’ (Boschma, 2017; Hidalgo et al., 2018). In this context, most empirical evidence supports the claim that regional economies mostly evolve through processes of related diversification, while processes of unrelated diversification are less common. Next to the concept of relatedness, a complementary perspective that captures whether regional diversification affects local capabilities is based on the concept of economic complexity (Hidalgo, 2021; Hidalgo and Hausmann, 2009). In this line of thought, complex industries or technologies are associated with economic growth. Though desirable, entering complex industries is far from easy for most regional economies. Based on these insights, recent works suggest the ‘high road’ to industrial development is one that privileges entry in sectors that are both related to the local industry mix and relatively more complex (Balland et al., 2019).

In this paper, we contribute to this debate by studying whether regional external linkages can activate processes of local diversification that modify the technological and industrial portfolio of local economies in the case of emerging countries. Although often overlooked by the regional diversification literature (Yeung, 2021), external linkages (such as return migrants, foreign direct investment, import, interregional co-inventor networks) represent important avenues to access novel and non-redundant knowledge and can activate local diversification processes (Morrison, 2023; Zhu et al., 2017). External linkages, hence, can close the knowledge gap and reduce the risk associated with entering unrelated sectors, in particular in the case of emerging economies. For these economies, a path-breaking process of diversification (i.e. developing more complex and unrelated activities) might be a more plausible strategy to follow in order to catch up with advanced industrial leaders. In fact, though deviations from the path are rare, historical evidence shows they have been successful in the past (Lee and Malerba, 2017; Pinheiro et al., 2022). Hence, a potential diversification path for regions in emerging countries may materialize by targeting unrelated activities at the right time, rather than always pursuing the most related trajectories of local industrial development (Alshamsi et al., 2018; Hidalgo et al., 2018). Furthermore, emerging economies often lack the internal capacity to endogenously generate a portfolio of technological and industrial competences that can be used to upgrade the economic complexity of the domestic productive structure. Hence, external linkages may provide them with an opportunity to intercept more sophisticated non-local knowledge assets.

Against this backdrop, this work specifically investigates how foreign multinational enterprises (MNEs), as global actors able to connect regions at multiple geographical scales, represent a source of external knowledge that facilitate the process of regional diversification in the case of China. In doing so, we develop an original theoretical framework integrating insights from studies on regional diversification and economic complexity with the literature on MNEs. This represents a key conceptual contribution that allows us to define, measure and compare different regional diversification trajectories connected to the presence of foreign MNEs, starting from those that are safer (in related sectors) to those that are apparently riskier (in unrelated sectors) and explore the role of MNEs under these different scenarios.

MNEs have been specifically regarded as key actors for regional structural change, as they have the resources and capabilities to trigger unrelated diversification (Ascani and Iammarino, 2018; Elekes et al., 2019; Iammarino and McCann, 2013; Revilla Diez and Berger, 2005). For example, in a detailed case study, Qin et al. (2021) show that the entry of MNEs with advanced technology related to industrial robots has enabled the Shunde District (in Foshan City, Guangdong Province, China) to establish a specialization in the robotic industry, which is technologically complex and less dependent on the local pre-existing capabilities. MNEs, in fact, can mobilize firm-internal resources and

capabilities in their home regions through their intra-corporate networks (Letto-Gillies, 2012). Thus, from the perspective of the recipient region, hosting a foreign MNE can serve as a global channel to bring in new and advanced technologies as well as managerial practices (Ernst and Kim, 2002; Javorcik, 2004; Rojec and Knell, 2018).

The context of China is particularly relevant to explore these questions. China is an Eastern Asian post-communist transition country, in which the legitimacy of communist government is mainly based on economic development after the reform and opening-up in the late 1970s. Due to the GDP-oriented performance appraisal mechanism of Chinese official promotion system, local governments compete fiercely with each other to attract MNEs to invest in their own regions. Among other strategies to promote economic development, such as improving local firms' innovative capabilities or cultivating local human capital, attracting foreign MNEs is a fundamental and efficient way to achieve rapid economic growth in the short run (Zhang and Cai, 2020). In October 1986, the central government promulgated the *Regulations on Encouraging Foreign Investment*, which provides plenty of preferential policies, including taxation, land use fees, credit, foreign exchange and import and export procedures, for foreign MNEs. Subsequently, local governments have also formulated supporting rules in accordance with the regulations to attract MNEs, especially those which could promote the development of focus industries outlined in the 5-year plans for the national economic and social development. As He (2021: 644) observed, MNEs have substantially transformed the local industrial structure and initiated new development paths for Chinese regions. However, it remains unclear what types of regional diversification MNEs have induced in China. We carry out our analysis during the period 1998–2007. In this period the inflow of MNEs increased significantly, from 45.46 billion dollars to 83.52 billion dollars and accounted for more than half of the total import and export value of China (Ministry of Commerce, People's Republic of China, 2020). Our results show that the presence of MNEs is positively and significantly correlated with the industry entry in Chinese regions, and specifically, the entry of unrelated and complex industries, and these results are robust under a series of robustness checks.

Our findings not only suggest that the region's external linkages provided by MNEs can be a catalyst of local diversification, but also that foreign MNEs can concomitantly activate a process of upgrading of local technological and industrial activities towards more complex competences that are otherwise unavailable within the regional economy, thus allowing locations to diversify into relatively more complex sets of activities. This is a specific pathway of regional diversification that we name 'leapfrogging' trajectory, because of the opportunities it delivers in terms of accessing novel and more sophisticated knowledge through the external linkage represented by MNEs.

This work contributes to different strands of literature. As mentioned above, it adds to the literature on regional diversification and relatedness by investigating the role of external linkages in the context of emerging countries. It also contributes to the literature on MNEs and industrial development in China (He, 2008; He et al., 2012; He and Zhu, 2019), by providing fresh evidence on the interplay between foreign MNEs and the local economy in terms of different types of diversification processes. We believe this evidence is also useful to inform policy debates on attraction strategies of foreign direct investment (FDI) in the context of emerging economies.

The paper is structured as follows. Section 'Theoretical background' presents the theoretical framework. Section 'Data and methodology' illustrates the data. The proposed methodology is presented in section 'Estimation approach'. Section 'Results' discusses the empirical findings. Section 'Concluding remarks' concludes.

## **Theoretical background**

### *Regional relatedness and economic complexity*

Well-grounded empirical evidence in economic geography has shown that new economic activities do not appear at random in space; rather, they tend to follow a path-dependent process (Boschma and

Martin, 2007). This suggests that regions develop new activities in sectors that are related to those already existing in the local area (Boschma, 2017; Hidalgo et al., 2018). This process of related diversification has been observed in a variety of geographical and institutional settings at the micro, meso and macro level. For example, Klepper's seminal work on the formation of the Detroit automobile cluster showed that spin-offs and start-ups in related industries played a pivotal role in the emergence of the new car industry in the region (Klepper, 2007). For the case of Spanish regions, Boschma et al. (2013) found that new entries appear in industries in which the region is already specialized. In the case of China, using firm level data, He et al. (2018) found significant evidence that regions branch into new industries that are technologically related to the existing industries. This is further consolidated by several other studies with Chinese export and import data (Chen et al., 2017; He and Zhu, 2019; Hidalgo, 2021; Zhu et al., 2017). Besides the positive impact of related economic activities, Gao et al. (2021) also verified the positive effect of the spatial spillovers of neighbouring regions in China's regional diversification. At the macro level, Hidalgo et al. (2007) suggested that countries export new products that are related to those in which they had already a comparative advantage. Moreover, what has been observed for industries and products seems to hold also for technologies (Boschma et al., 2015; Rigby, 2015) and scientific fields (Guevara et al., 2016).

Countries or regions do not only diversify in new activities, but also aim at upgrading their industrial and technological portfolio (Bell and Pavitt, 1995; Malerba and Nelson, 2011). Higher levels of economic complexity have been associated with higher levels of income (Hidalgo and Hausmann, 2009) and economic growth (Hausmann et al., 2014). Therefore, a complementary aspect to the process of regional diversification concerns the sophistication or complexity of the industrial and technological paths followed by countries and regions. However, it has been noted that climbing the ladder of complexity is a risky endeavour (Balland et al., 2019), especially for emerging countries or peripheral regions, which tend to have a limited internal portfolio of capabilities as compared to advanced economies (Petralia et al., 2017). Recent evidence indeed shows that regions can be stuck in a 'low-complexity trap', whereby only those regions who already developed high-complexity activities are capable to diversify further around these activities, while the others may fail to upgrade (Pinheiro et al., 2022). In this context, then, a fundamental question regards the factors that allow regions to escape this slow-road to development and instead grow into more complex and unrelated activities.

### *Regional external linkages: The role of foreign MNEs*

The growing strand of works focusing on the role of regional external linkages in the process of local economic development provide various hints to address this issue. These studies, in fact, suggest that external connections help regions to escape lock-in by tapping into novel and non-redundant knowledge (Boschma, 2021b; Giuliani et al., 2005; Morrison et al., 2013). The nature of these linkages can be rather heterogeneous, ranging from inter-regional inventors' collaboration (Balland and Boschma, 2021; Whittle et al., 2020) and import-export relations (Andersson et al., 2013), to regional cooperation (Santoalha, 2019), migration flows (Migueluez and Morrison, 2023) and investments by MNEs (Castellani et al., 2022; Elekes et al., 2019), among others. All these channels may bring to the region the missing capabilities needed to unlock the local innovation potential and in turn enable a process of unrelated diversification.

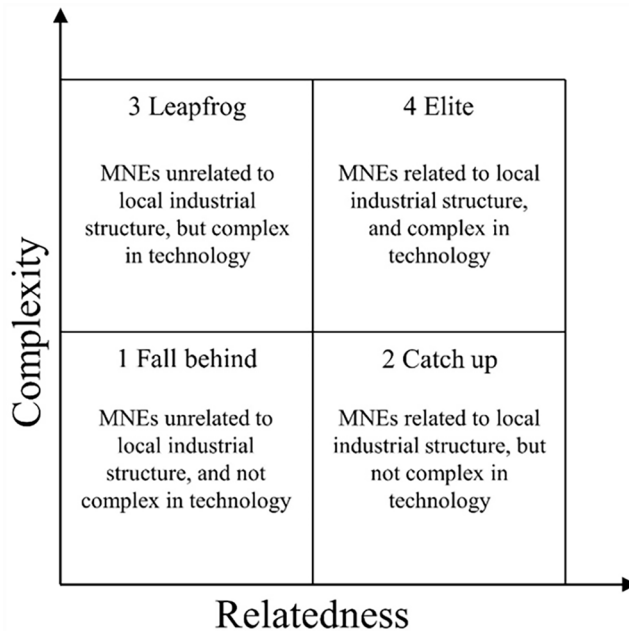
In this framework, the specific external linkage provided by MNEs is particularly relevant, as their activities across borders tend to be stable once an investment is undertaken, as compared to other typologies of regional external linkages that may be more volatile or more subject to changing market conditions. Furthermore, the presence of foreign MNEs may produce an upgrading of regional capabilities through different forms of interaction with local incumbent firms. When expanding internationally, in fact, MNEs become carriers of knowledge (also in the form of human capital), technology, organizational and managerial routines (Alfaro, 2017; Crespo and Fontoura, 2007) and these

advantages can be disseminated to domestic companies in host markets through both market- and nonmarket-mediated mechanisms (Ernst and Kim, 2002). In this respect, a wide literature has investigated various channels through which the interaction between foreign MNEs and local firms may produce a transmission of knowledge, technologies, competences and capabilities among organizations (for a review see Rojec and Knell, 2018). These mechanisms may include inter-industry spillovers through forward and backward linkages with customer and suppliers, as well as intra-industry effects via competition dynamics, demonstration, reverse engineering, labour training and workers' mobility (Fosfuri et al., 2001; Görg and Greenaway, 2004; Iammarino and McCann, 2013; Javorcik, 2004; Lu et al., 2016; Poole, 2013).

Consistently, recent works suggest MNEs can play a relevant role for regional diversification processes. In fact, the interaction between MNEs and local companies can produce new diversification opportunities for local incumbents, as suggested by a growing number of studies. For example, looking at the case of Hungary, Elekes et al. (2019) found that, compared with domestic companies, MNEs tend to show greater deviations from the regional average capabilities, thus triggering a process of unrelated diversification at the regional level. Using Turkish manufacturing firm data, Lo Turco and Maggioni (2019) further show that MNEs contribute to raise the product complexity of host regions by transferring locally unavailable knowledge. With a focus on Italian regions, Ascani et al. (2020) suggested that, along with internal specialization, local MNEs' external linkages can also promote regional innovation by bringing external knowledge inputs into the regional economy. With a focus on green FDI, Castellani et al. (2022) show that foreign investment is a source of technological diversification in the case of EU regions. Using Chinese export data, Zhu et al. (2017) argue that extra-regional linkages in the form of FDI and imports enhance product unrelated diversification. These mechanisms tend to be more relevant, the more the economic structure of recipient economies is related to the sector profile of MNEs (Cortinovis et al., 2020; Howell, 2020); the underlying motive being that a high degree of cognitive proximity is essential in the process of knowledge diffusion and absorption. Therefore, domestic firms can generally benefit more from the presence of MNEs when the latter operate in industries that are complementary to the local economic profile in terms of knowledge base (Cantwell and Iammarino, 2005).

### *Foreign MNEs and the different trajectories to diversification*

Despite the burgeoning evidence reviewed above, it remains unclear whether and under which circumstances external linkages can activate processes of regional diversification that modify the industrial structure of local economies. In order to unveil these mechanisms, we combine the role of industrial relatedness and knowledge complexity into one single framework. In doing so, we are able to explore the role foreign MNEs may play in the industrial development of Chinese regions. For this purpose, we adapt the conceptual framework of Balland et al. (2019), where regions face four diversification scenarios, which are shaped by two dimensions: relatedness and complexity, as represented in Figure 1. This space represents activities that are not yet present in the region, and can be either more (less) complex or related to those already existing in the region. Regions moving to sectors that are above the average complexity line will upgrade their industrial structure, as these activities will be more complex than they used to have. However, the likelihood of developing them also depends on the degree of relatedness with the existing industrial structure, which is measured along the *relatedness* axis (i.e. *x* axis). The further away regions are from the average relatedness, the harder and riskier is for them to develop such activity. In this context, MNEs can moderate the effect of relatedness and enhance structural change, but they can also reinforce existing regional specialization, so impeding structural change. For example, Quadrant 2, which is below the average complexity line, illustrates a typical case of an emerging economy that develops a strategy of industrial development along a path dependent trajectory. New industries tend to be in sectors related to the existing ones, and allow only



**Figure 1.** Four diversification scenarios.

limited upgrading. In this context the presence of foreign MNEs can either reinforce domestic specialization or in the best-case scenario it allows to develop relatively more complex activities over-time. If this latter case would prevail and is consistent over time, a ‘catch up’ development process is likely to emerge in Quadrant 2, whereby MNEs’ competences are strongly related to the pre-existing regional bundle of low complexity capabilities. In this context, local industrial development may follow a slow but consistent pathway based on shared knowledge-bases between the capabilities introduced by foreign MNEs and the local economic structure. On the other hand, MNEs may also lead to a low-end trap in regional development (Castellani and Zanfei, 2003; Crescenzi and Iammarino, 2018; Narula and Marin, 2003; Trippl et al., 2018), when regions lack appropriate human capital and institutional environment to absorb and reconfigure the knowledge, technologies, and managerial know-how brought in by MNEs (Dunning and Lundan, 2008). In the case of China, though FDI has generally improved the country’s technological capabilities (Long, 2005), some lagging regions tend to attract MNEs with preferential policies without evaluating their local resources and capabilities, as a result of which, the agglomeration of MNEs is only an isolated enclave for regional economy and contributes little to industrial upgrading. Usually, MNEs attracted by appealing preferential policies tend to be footloose and badly coupled with regional assets (Görg and Strobl, 2003). Moreover, MNEs could also crowd out domestic firms due to their advantages in export markets, technology and capital (Görg and Greenaway, 2004; Rojec and Knell, 2018), and weaken the endogenous innovative capabilities of hosting regions. In these situations, the agglomeration of MNEs may lead to the lock-in of regional economy in low-end activities.

Quadrant 1 identifies a scenario where there are limited options for the region, and all are relatively risky as all missing activities are unrelated to those present in the region. In this case, the interaction between foreign MNEs and local actors is limited to activities with low complexity. This scenario is the one that typically emerges in peripheral economies, which attract foreign investments that exploit local cost advantages or resources, but develop activities in fields that are further away from the capabilities present in the region. In this sense, foreign MNEs in the region may be scattered in many different activities that do not lead to the development of a local industrial fabric based on shared



competences. In such a case, we can foresee a ‘falling behind’ trajectory. On the other side of the spectrum, two high roads to industrial development are conceptually possible (Quadrants 3 and 4). A first trajectory implies that foreign MNEs carry more complex activities and competences that are related to their existing regional portfolio (Quadrant 4). Clearly, this is a scenario that can be found in already complex economic systems, most likely in advanced economies, where domestic companies are generally at close reach from a varied and sophisticated portfolio of technologies and capabilities. This is not however the most likely scenario in emerging economies, and therefore we name it ‘elite’ trajectory in the setting of this study. Our attention goes instead to what Balland et al. (2019) labelled the ‘casino’ strategy, that in the context of the present paper we relabel ‘leapfrogging’ trajectory to highlight the opportunities it brings about for an emerging economy (Quadrant 3). In these circumstances, indeed, foreign MNEs may become the channel through which recipient regions can access a diverse set of external capabilities that are unavailable locally and that are characterized by relatively high degrees of complexity. In other words, external actors, such as MNEs in the case of China, reduce the risk associated to developing activities that are unrelated to the existing portfolio, and facilitate a trajectory of diversification of local knowledge assets by introducing and stimulating activities that are relatively novel and complex in a given regional economic system. From a regional perspective, therefore, hosting foreign MNEs may provide the grounds to access locally scarce knowledge assets that are instrumental for the upgrading of the existing technological and industrial portfolio of the local economy.

These potential trajectories offer a conceptual outline of the opportunities produced by foreign MNEs in terms of local economic processes of diversification and technological upgrade. Nonetheless, several contingencies may characterize the relationship between the presence of foreign MNEs and the local processes of industrial diversification and upgrade. In this respect, the literature suggests that a certain degree of complementarity between the profile of MNEs and the local industry structure can be beneficial for local knowledge dissemination (Ernst and Kim, 2002; Yeung, 2021), as local incumbents can more easily intercept and absorb capabilities if they share the same knowledge base as foreign MNEs (Iammarino and McCann, 2013; Rojec and Knell, 2018). Therefore, the varying extents to which foreign MNEs are related to the local industry structure may asymmetrically shape the different trajectories of regional diversification discussed above. Plausibly, a trajectory of unrelated diversification into more complex activities (i.e. leapfrogging) would require accessing a larger spectrum of external capabilities than those already present in a region. Furthermore, MNEs may be operating in sectors in which the pace of technological change differs substantially (Ascani and Gagliardi, 2020; Iammarino and McCann, 2013). Hence, industries where knowledge plays a predominant role to maintain a competitive edge may be characterized by more fertile local diversification and upgrading opportunities, as compared to those in sectors where knowledge is less critical (Ang, 2008; Hill and Rothaermel, 2003).

The diversification trajectories depicted in Figure 1 are also shaped by contextual factors, and in the case of China in particular by the role of industrial policies. In order to ensure that FDIs could better serve China’s economic development, the Chinese government released the Catalogue of Industries for Guiding Foreign Investment in 1995 for the first time. The Catalogue has specified the industry categories of FDIs that are encouraged or permitted to enter on the one hand, and the categories of FDIs that are restricted or prohibited on the other hand. During our sample period, due to China’s accession to the WTO, the 2002 revision of the Catalogue has significantly reformed the FDI regime by increasing the number of encouraged sectors from 186 to 262, and cutting the restricted industries from 112 to 75 (OECD, 2008). The high-tech manufacturing, environmentally-friendly technologies, energy and natural resource exploitation industries are especially encouraged (OECD, 2003). Although the Catalogue has been revised several times in the later years to accommodate the evolution of Chinese economy, the high-technology and knowledge-intensive manufacturing industries are consistently among the encouraged categories (Davies, 2013). The FDIs in the encouraged sectors are given favourable treatment because they comply with China’s industrial development

policies, which have continuously promoted high-technology, capital-intensive industries, as well as development in the underdeveloped inland regions (Davies, 2010). Fiscal incentives, such as tax reduction and cheap land, are often employed by local governments to attract FDIs in encouraged sectors (Jakubczak, 2020). All together, these circumstances seem to suggest that knowledge intensive sectors may play a considerable role in the diversification and upgrading process in Chinese regions.

In the remainder of this article, we will empirically investigate the role of foreign MNEs in facilitating (or hindering) the trajectories of diversification along the multifaceted lines described above.

## Data and methodology

### Data

Our empirical analysis relies on data extracted from the Annual Survey of Industrial Firms (ASIFs) 1998–2007 of the National Statistical Bureau of China.<sup>1</sup> Specifically, we exploit the rich firm-level information provided in this dataset by considering company location, 4-digit industry codes, number of employees and the total output value of companies with sales above 5 million Yuan. Following He et al. (2018), we only focus on manufacturing firms.

We followed the concordance table by Brandt et al. (2012) to match the industry codes of the period 1998–2002 (which were coded following the *Industrial classification for national economic activities GB/T4754-94*), with those of the period 2003–2007 (which were coding using the *Industrial classification for national economic activities GB/T 4754-2002*). In line with standard practices (Chen, 2018), we dropped observations that violate the common sense of accounting, that is, observations with a negative number of employees, negative industrial output or negative new product output, as well as the total paid-in capital not equal to the sum of its subcategories.

In order to identify MNEs in our data, we computed the share of paid-in capital from foreign countries and regions (including Hong Kong, Macau and Taiwan) for all firms. Following Dunning and Lundan (2008) and Elekes et al. (2019), a firm is regarded as a MNE if its share of paid-in capital from foreign countries and regions is higher than 50%, since in this case the foreign economic entity is de jure able to control the decision making in the company. Finally, based on the firm-level panel dataset, we computed industry-prefecture level data for 423 four-digit manufacturing industries of 331 prefectures.

### Measurement and methodology

**Dependent variable.** This paper investigates the relationship between foreign MNEs and the regional industrial diversification of Chinese prefectures. Hence, our dependent variable captures the different trajectory of diversification a region can enter, as illustrated in Figure 1. To construct these trajectories, we need to compute the revealed comparative advantage index (RCA), the measure of industry relatedness and the complexity index.

The concept of relatedness builds on the idea that highly co-occurring industries need similar requirements in terms of technology, capital, institutions and skills (Hidalgo et al., 2007). To compute the ‘relatedness’ matrix, we first consider the industries in which a prefecture specializes. An industry  $i$  in prefecture  $r$  in year  $t$  is considered to be specialized when it has a revealed comparative advantage ( $RCA_{i,r,t} = 1$ ).  $RCA_{i,r,t}$  is defined to be 1 when the location quotient of industry  $i$  in prefecture  $r$  in year  $t$  is larger than 1 ( $LQ_{i,r,t} > 1$ ), that is, the prefecture  $r$  has a higher percentage of employment in the industry  $i$  in year  $t$  ( $E_{i,r,t}$ ), as a share of its total employment, than the percentage of employment in industry  $i$  across all prefectures in year  $t$ . In more formal terms:



$$LQ_{i,r,t} = \frac{\sum_i E_{i,r,t}}{\sum_r E_{i,r,t} / \sum_{i,r} E_{i,r,t}} \tag{1}$$

and

$$RCA_{i,r,t} = \begin{cases} 1, & \text{if } LQ_{i,r,t} > 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

RCA is used to compute the main dependent variable, that is, *entry*. If industry *i* does not have a revealed comparative advantage (RCA) in prefecture *r* in year *t*−1, and has an RCA in year *t*, then *entry*<sub>*i,r,t*</sub> will be assigned the value 1, otherwise, if industry *i* still does not have an RCA in year *t*, *entry*<sub>*i,r,t*</sub> will be set to 0.

The RCA matrix (call it **M**) is a *K* × *N* matrix with prefectures as rows and industries as columns. It is also an input for calculating the relatedness between industries. The relatedness between two industries *i* and *j* in year *t* is the minimum of the pairwise conditional probabilities of a prefecture having an RCA in an industry given that it has an RCA in another one in year *t*.

$$relatedness_{i,j,t} = \min \left\{ P(RCA_{i,t} = 1 | RCA_{j,t} = 1), P(RCA_{j,t} = 1 | RCA_{i,t} = 1) \right\} \tag{3}$$

The result of above calculation is an *N* × *N* symmetric relatedness matrix between pairwise industries with all zeros on the main diagonal. In Figure A1 in Supplemental Appendix A, we show the relatedness heatmap between Chinese manufacturing industries in 1998/2001/2004/2007. In line with the finding of Hidalgo et al. (2007), the results show a matrix with high values (bright colouring) mainly along the diagonal, indicating some industries highly related with each other and unrelated with the rest. Following the strategy by Hidalgo et al. (2007), we define the relatedness density to measure the closeness that a new potential industry *i* to a prefecture’s current productive structure. It is given by formula (4) as below.

$$relatedness\_density_{i,r,t} = \frac{\sum_{j \neq i} RCA_{j,r,t} * relatedness_{i,j,t}}{\sum_{j \neq i} relatedness_{i,j,t}} \tag{4}$$

where *relatedness\_density*<sub>*i,r,t*</sub> is the density around industry *i* given the productive structure of the prefecture *r* in year *t*. The *RCA*<sub>*j,r,t*</sub> = 1 if prefecture *r* has an RCA in industry *j* in year *t*, and 0 otherwise. A high relatedness density value means that prefecture *r* has many developed industries surrounding the industry *i* in year *t*.

In order to define whether an industry is less related or more related to a prefecture’s productive structure, following the framework proposed by Balland et al. (2019), we calculate the prefecture relatedness density by taking the mean relatedness density of industries without an RCA in the prefecture (as shown in formula 5), and compare the relatedness density of an industry with the prefecture relatedness density (*prefecture\_relatedness\_density*<sub>*r,t*</sub>) to define whether this industry entry is path-breaking (path-dependent) or not. More in detail, if the relatedness density of the industry is lower

(higher) than the prefecture relatedness density, the industry entry is defined as a path-breaking (path-dependent) one.

$$prefecture\_relatedness\_density_{r,t} = \frac{\sum_i (1 - RCA_{i,r,t}) * relatedness\_density_{i,r,t}}{\sum_i (1 - RCA_{i,r,t})} \quad (5)$$

Once relatedness is computed, we turn our attention to the knowledge complexity of industries. Following the method proposed by Hidalgo and Hausmann (2009) and developed by Cristelli et al. (2013), Balland and Rigby (2017), Mealy et al. (2019) and Balland et al. (2019), we first row-standardize the RCA matrix ( $\mathbf{M}$ ) and its transpose ( $\mathbf{M}_t$ ). Multiplying  $\mathbf{M}_t$  and  $\mathbf{M}$  gives a squared matrix ( $\mathbf{B} = \mathbf{M}_t \times \mathbf{M}$ ) with the dimension equal to the number of industries. The knowledge complexity index of these industries is given by the eigenvector which is associated with the second largest eigenvalue (call it  $\mathbf{KCI}$ , which is an  $N \times 1$  vector) of the squared matrix ( $\mathbf{B}$ ). In order to be able to compare the complexity index between different years, we standardize the complexity index ( $\mathbf{KCI}$ ) by subtracting its mean and dividing it by its standard deviation. Then we rescale the complexity index to range from 0 to 100. In Table B1 in Supplemental Appendix B, we show the top and last 10 most complex industries. Not surprisingly, electrical machinery and equipment manufacturing, computer and other electronic equipment manufacturing, and office machinery manufacturing have the highest degree of complexity, whereas, agricultural and side-line food processing and non-ferrous metal smelting are among the least complex industries. Following Zhou and He (2018) and Li and He (2021), we calculate the knowledge complexity of a prefecture by taking the average knowledge complexity of industries with an RCA in the same prefecture. In a more formal way,

$$prefecture\_complexity_{r,t} = \frac{\sum_i RCA_{i,r,t} * KCI_{i,r,t}}{\sum_i RCA_{i,r,t}} \quad (6)$$

where  $prefecture\_complexity_{r,t}$  is the knowledge complexity of prefecture  $r$  in year  $t$ , and  $KCI_{i,r,t}$  is the knowledge complexity of industry  $i$  in prefecture  $r$  in year  $t$ . In Figure A2 in Supplemental Appendix A, we plot Chinese prefectures' complexity in 1998/2001/2004/2007, and the spatial distribution of prefecture complexity is quite in line with the level of economic development across Chinese regions, showing a gradient descent pattern from the Eastern coastal area to the Western inland area. In order to define whether an industry entry has higher (lower) complexity or not, we compare the complexity of an industry with its prefecture complexity in the corresponding year. More in detail, if the industry complexity is higher (lower) than the prefecture complexity, then the industry entry is defined as of 'higher complexity' ('lower complexity') one.

Following Balland et al. (2019), along with  $prefecture\_relatedness\_density$ , we can have a classification containing  $2 \times 2 = 4$  types of diversification, as shown in Figure 1: lower relatedness density and higher complexity (leap) corresponds to the 'leapfrogging' trajectory; lower relatedness density and lower complexity (fall) corresponds to 'falling behind' trajectory; the higher relatedness density and higher complexity (elite) corresponds to the 'elite' trajectory and higher relatedness density and lower complexity (catch) to the 'catch up' trajectory. All industries across all prefectures during the sample year could be classified into one specific type. Based on this classification, we build a set of additional entry dependent variables. For instance, industry  $i$  in prefecture  $r$  at year  $t-1$  is 'leap' type, if it does not have an RCA in year  $t-1$  and has an RCA in year  $t$ , then  $entry\_leap_{i,r,t}$  is assigned value 1, otherwise 0. The same rule also applies to the rest types,  $entry\_fall$ ,  $entry\_elite$  and  $entry\_catch$ . This is equivalent to splitting the variable  $entry_{i,r,t}$  by the four types (leap, fall, elite, catch) in year  $t-1$  respectively.

**Foreign MNEs.** We measure the presence of MNEs in a given industry-prefecture using the share of MNEs over the total number of firms in an industry-prefecture in a given year. Following Cortinovis et al. (2020), we construct the variable *relMNE* by calculating the weighted share of MNEs in the related industries of the focal industry. We only consider the related industries with an RCA, since they are relatively large in size and mature in terms of capabilities. This is achieved by the following formula (7). Then, we rescale *relMNE* to range between 0 and 1 by dividing itself with its maximum value, and this will not change the relative size of *relMNE* between different prefectures and industries.

$$relMNE_{i,r,t} = \sum_{j \neq i} relatedness_{i,j,t} * (MNE_{j,r,t} * RCA_{j,r,t}) \quad (7)$$

## Estimation approach

We use a linear probability model to test the following empirical relationship:

$$entry_{i,r,t} = \beta_1 MNE_{i,r,t-1} + \beta_2 relMNE_{i,r,t-1} + \beta_3 relatedness\_density_{i,r,t-1} + \gamma control_{i,r,t-1} + \alpha_{i,r} + \tau_t + \epsilon_{i,r,t} \quad (8)$$

where *entry*<sub>*i,r,t*</sub> is our main dependent variable as defined above. We perform our model on annual data. The key explanatory variable *MNE*<sub>*i,r,t-1*</sub> indicates the presence of MNEs as defined above in industry *i*, prefecture *r* and year *t-1*. The second key explanatory variable *relMNE*<sub>*i,r,t-1*</sub> represents the weighted share of MNEs in the related industries of the focal industry *i*, in prefecture *r*, year *t-1*. Following the literature on regional industry evolution (Boschma et al., 2015), we also include relatedness density (*relatedness\\_density*<sub>*i,r,t-1*</sub>) as a control variable.

We further include several other covariates in the vector of controls. We account for cross-regional spillover effects from neighbouring prefectures by means of *neb\\_relatedness\\_density*, that is the average relatedness density of the focal industry in the neighbouring prefectures of the focal prefecture; *nebMNE* is the average share of MNEs in the focal industry in the neighbouring prefectures. The neighbouring prefectures of the focal prefecture are defined as those sharing a common border with the latter. In order to control for the innovative capability of an industry in a prefecture, we also obtain the patent application information of sample firms from EPS database, which is one of the largest and most comprehensive Chinese data providers and has matched ASIF firm data with CNIPA (China National Intellectual Property Administration) patents data. Aggregating the patent application data at industry-prefecture level enables us to get the explanatory variable *patent*. The variable *population* controls the population size (10,000 persons) of a prefecture, while, *pcGDP* stands per capita GDP (Yuan per capita), which is used to proxy the level of economic development in a prefecture. We further control for regional agglomeration economies by adding *pop\\_density*, which is measured by the number of population per square kilometre. We also include the prefecture level of education measured as the percentage of college students in the total population (*human\\_capital*), as the level of human capital can influence a prefecture's capability to absorb new knowledge and technology. The presence of regional infrastructure is also included with the variable *pc\\_road*, which is defined as the per capita road area (square metre) in a prefecture. All these prefecture level variables are from *China City Statistical Yearbook 1999-2007* (for short, CCSY). We also control two industry level variables, namely the industry size proxied by the total number of employees in an industry (*employment*), and the concentration degree of an industry with Herfindahl-Hirschman index (*herfindahl*) to account for the sectors' market structure. Furthermore, we also include industry-prefecture ( $\alpha_{i,r}$ ) and year ( $\tau_t$ )

**Table 1.** The descriptive statistics of main variables.

Variables	Source	No. of observations	Min	Median	Max	Mean	Std. Dev
entry	ASIFs	1,088,611	0.000	0.000	1.000	0.028	0.165
entry_leap	ASIFs	529,631	0.000	0.000	1.000	0.012	0.106
entry_fall	ASIFs	64,009	0.000	0.000	1.000	0.022	0.147
entry_elite	ASIFs	272,758	0.000	0.000	1.000	0.038	0.190
entry_catch	ASIFs	222,213	0.000	0.000	1.000	0.057	0.232
MNE	ASIFs	1,400,130	0.000	0.000	1.000	0.028	0.136
relMNE	ASIFs	1,400,130	0.000	0.009	1.000	0.034	0.073
relatedness_density	ASIFs	1,400,130	0.000	0.131	1.000	0.144	0.094
neb_relatedness_density	ASIFs	1,400,130	0.000	0.143	0.549	0.146	0.075
nebMNE	ASIFs	1,400,130	0.000	0.000	1.000	0.013	0.054
patent (ln)	EPS	1,400,130	0.000	0.000	9.194	0.036	0.271
population (ln)	CCSY	1,049,886	2.770	5.889	8.082	5.856	0.665
pcGDP (ln)	CCSY	1,049,886	7.401	9.109	12.677	9.198	0.749
pop_density (ln)	CCSY	1,049,886	1.548	5.922	7.904	5.770	0.844
human_capital	CCSY	1,049,886	0.000	0.375	11.017	0.872	1.368
pc_road (ln)	CCSY	1,049,886	-3.912	1.758	4.159	1.730	0.648
employment (ln)	ASIFs	1,400,130	4.304	10.980	15.166	10.873	1.410
herfindahl	ASIFs	1,400,130	0.007	0.055	1.000	0.080	0.089

Due to the existence of zeros, we use the  $\ln(x + 1)$  transformation for variable *patent*. This also applies to the following regression tables.

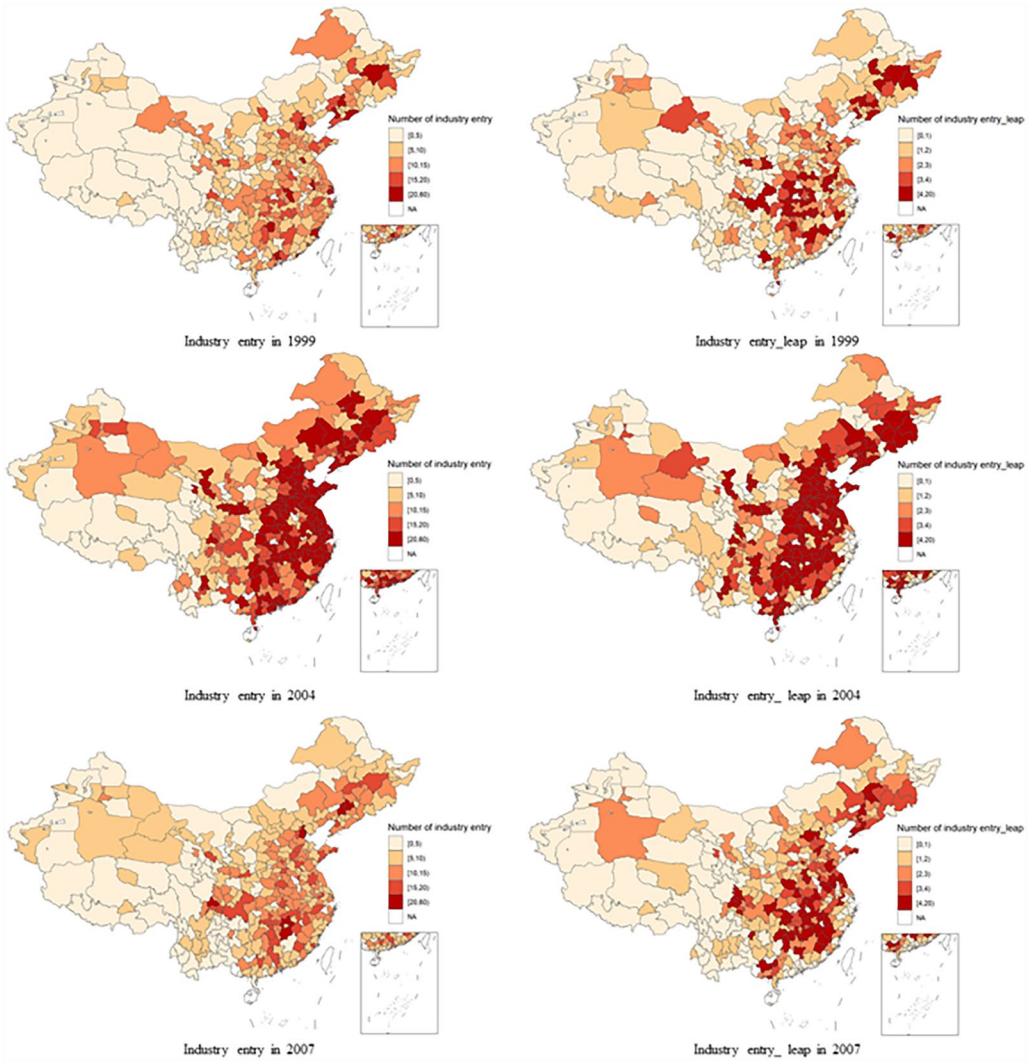
fixed effects. We use robust standard errors clustered at prefecture level to address the potential auto-correlation and heteroscedasticity in the error terms. The final dataset contains 279 prefectures and 423 industries. The descriptive statistics and data sources of our variables are presented in Table 1, while Table B2 in Supplemental Appendix B presents the matrix of correlation coefficients.

## Results

### Descriptive analysis

In this section, we present the general trends of industry diversification of Chinese prefectures. The average number of industry *entry* is shown in Table B3 in Supplemental Appendix B. During the period 1998–2007, Chinese prefectures seem to have experienced a drastic change in their industrial structure. In 1999, Chinese prefectures entered 8.35 industries on average, and this process peaked in 2004 with 17.70 entries. Entry dynamics rapidly slowed down to about 8.5 entries in the next following years. This inverted U-shape trend is related to the China's accession to the WTO in 2001, which led to a large influx of FDI. These investments dramatically accelerated the industrial diversification process in Chinese prefectures. The process was not evenly distributed across Chinese regions however. As shown in Figure 2, the Eastern region showed highest frequencies of industry entry, which is followed by the Central region, while the Western region showed the lowest entry dynamics.

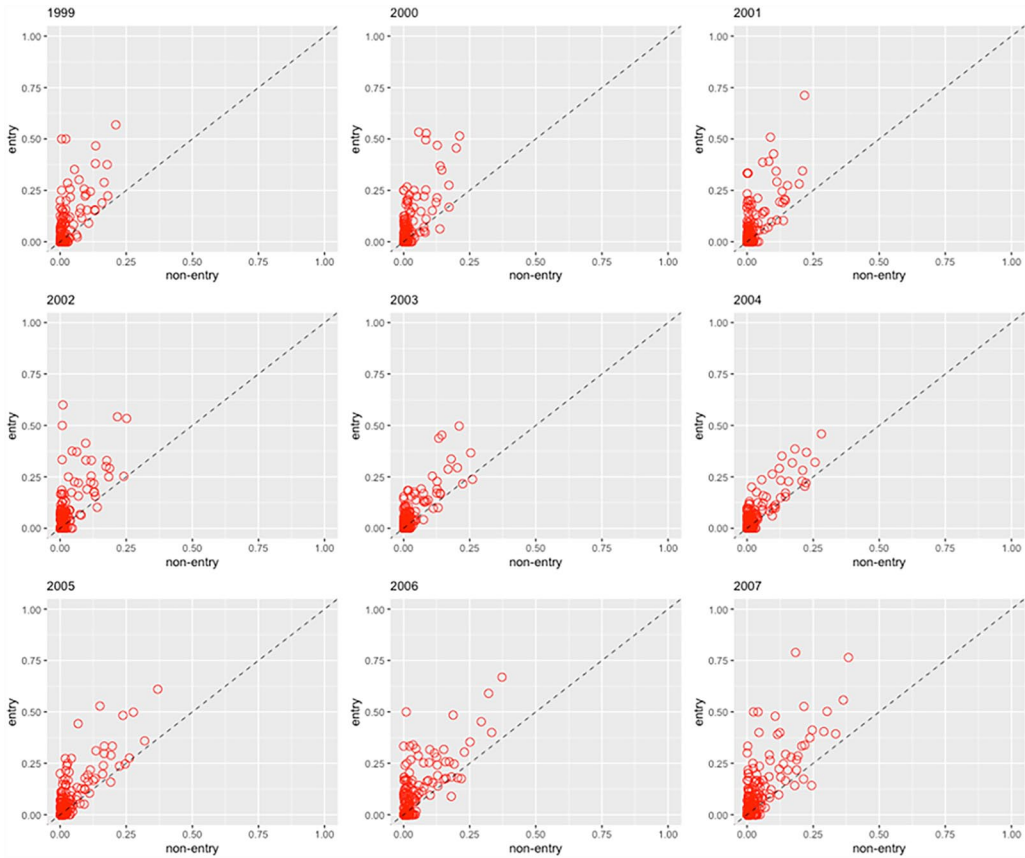
We also compute the number of industry entries for the four entry types (see Table B4, Supplemental Appendix B). We observe that related diversification (*entry\_elite* and *entry\_catch*) accounts for 75.39% of the total industry entries (22,931 in 30,418), which is in line with the evidence showing a path-dependent diversification process (Boschma, 2017). Among the unrelated diversification types, *entry\_leap* has a relatively large share, it indeed accounts for 20.14% of the total industry entries. The average number and spatial distribution of industry *entry\_leap* of Chinese prefectures are shown in Table B4 in Supplemental Appendix B and Figure 2 respectively. They show a pattern similar to the industry *entry* in general.



**Figure 2.** The spatial distribution of industry entry and entry\_leap in Chinese prefectures in 1999, 2004 and 2007.

To further explore the relationship between industry entry and share of MNEs, Figure 3 shows the average share of MNEs for entry and non-entry industries for all prefectures during our sample period. The horizontal axis represents the average share of MNEs of all non-entry industries for prefectures, and the vertical axis represents the average share of MNEs for all entry industries. The diagonal line is the dividing border where the average share of MNEs of all non-entry industries is equal to the average share of MNEs for all entry industries. When a prefecture is in the upper area of the diagonal, it means that the average share of MNEs of all entry industries is larger than the average share of MNEs of non-entry industries in the same prefecture. The distribution of regions in Figure 3 shows that most prefectures are in the upper area of the diagonal, which indicates that, systematically, entry industries have higher shares of MNEs than non-entry industries. We further apply this scatterplot analysis to industry entry\_leap in Figure 4, and the results show quite similar pattern, that is, entry\_leap industries tend to have higher shares of MNEs than non-entry\_leap industries.

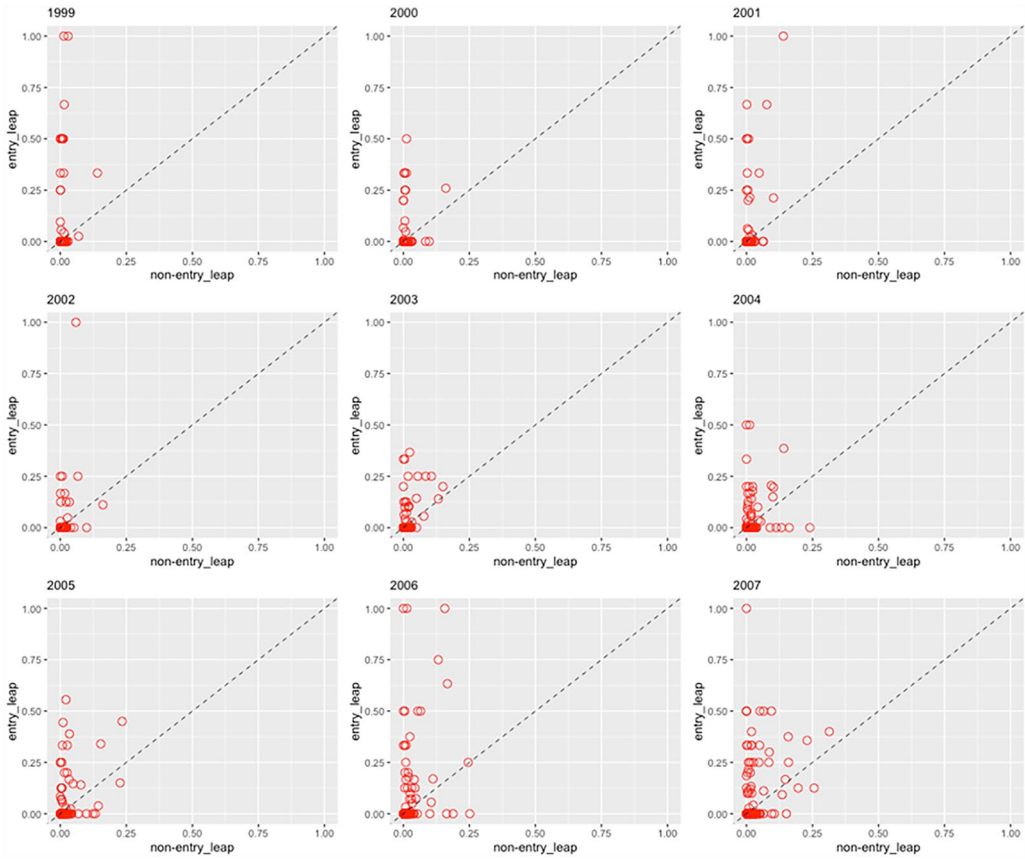




**Figure 3.** The average share of MNEs of industries that enter and do not enter in Chinese prefectures.

### Empirical results

The results of the regression analysis are reported in Table 2. In columns 1–4, the dependent variable is industry *entry*; in columns 5–8, we specifically investigate the four types of industry entry defined above: *entry\_leap*, *entry\_fall*, *entry\_elite* and *entry\_catch*. These reflect the four alternative trajectories envisaged in the conceptual framework outlined in Figure 1. In all models, we control for prefecture-industry and year fixed effects, in order to account for unobserved shocks at the local, sector or year level that may influence industry entries in our sample. The baseline estimates in columns 1 and 2 include our key independent variables (i.e. *MNE* and *relMNE*) without controls. Both their coefficients are positive and highly significant, thus suggesting that the presence of foreign MNEs both in the same and related industries may favour new industry entries within Chinese prefectures. Nonetheless, the magnitude of the relationship between industry entry and the activities of foreign MNEs in related sectors to the local industry base is sensibly larger than that of foreign MNEs operating in the same industries present in a prefecture. This initial evidence suggests that the advantages delivered by MNEs are more pronounced for sectors that, while sharing the knowledge base of the local industry structure, are also characterized by a certain degree of cognitive distance from it. In columns 3 and 4, our variables of interest remain positive and significant even after the inclusion of a full battery of control variables. Turning to the study of the specific trajectories conceptualized in section ‘Theoretical background’, in column 5, we specifically study the ‘leapfrogging’ trajectory.



**Figure 4.** The average share of MNEs of industries that enter and do not enter ‘leap’ type in Chinese prefectures.

Column 6 is associated with the ‘falling behind’ trajectory. Columns 7 and 8 are instead associated with the ‘elite’ and ‘catch up’ scenarios, respectively. Interestingly, the positive and significant impact of MNEs in related sectors holds only in the case of the leapfrogging scenario (column 5). In other words, the operations of MNEs in sectors that do not overlap with the local industry mix, but are related to it, may feed a local process of unrelated diversification in more complex economic activities. Furthermore, comparing the magnitude of the coefficients of *MNE* and *relMNE* in column 5 denotes again that the potential benefit of hosting MNEs in related sectors is notably larger than the advantage of receiving MNEs that replicate existing activities in the local economy. These findings are consistent with prior evidence showing that region’s external linkages provided by MNEs can be a catalyst of diversification (Castellani et al., 2022; Elekes et al., 2019; Zhu et al., 2017). Our results, however, further suggest that these diversification opportunities become particularly relevant in the context of emerging economies when the presence of foreign MNEs can concomitantly activate a process of upgrading of local technological and industrial activities towards more complex competences that are otherwise unavailable within the regional economy.

**Regional diversification and industry heterogeneity in knowledge content**

While the analysis above provides a general insight on the role of foreign MNEs in the framework of different trajectories of diversification and upgrade of local economic structures, a further

**Table 2.** The effect of MINE presence on industry entry.

	Dependent variable								
	entry	(1)	(2)	(3)	(4)	(5)	entry_fall	entry_elite	entry_catch
MINE		0.040*** (0.004)	0.039*** (0.004)	0.036*** (0.004)	0.036*** (0.004)	0.042*** (0.009)	0.009** (0.004)	0.047*** (0.009)	0.035*** (0.007)
relMINE		0.106*** (0.026)	0.106*** (0.026)	0.036*** (0.004)	0.084*** (0.028)	0.120*** (0.037)	0.021 (0.036)	0.083 (0.057)	0.039 (0.049)
relatedness_density		0.203*** (0.018)	0.184*** (0.020)	0.194*** (0.022)	0.178*** (0.024)	0.099*** (0.024)	0.086* (0.048)	0.173*** (0.043)	0.209*** (0.036)
neb_relatedness_density		0.244*** (0.026)	0.248*** (0.026)	0.231*** (0.031)	0.238*** (0.032)	0.099*** (0.031)	0.119* (0.072)	0.361*** (0.066)	0.265*** (0.061)
nebMINE				0.015* (0.008)	0.011 (0.008)	-0.007 (0.012)	0.014 (0.022)	-0.012 (0.017)	0.038 (0.023)
patent (ln)				0.013*** (0.003)	0.013*** (0.003)	0.013 (0.008)	0.014*** (0.005)	0.001 (0.007)	0.015*** (0.005)
population (ln)				0.005 (0.005)	0.006 (0.005)	0.006 (0.004)	-0.021** (0.010)	-0.010 (0.015)	0.030** (0.013)
pcGDP (ln)				0.011*** (0.003)	0.011*** (0.003)	0.005** (0.002)	0.003 (0.007)	0.012* (0.006)	0.022*** (0.007)
pop_density (ln)				0.007** (0.003)	0.009*** (0.003)	0.007** (0.003)	-0.021*** (0.007)	0.004 (0.014)	0.021** (0.010)
human_capital				-0.001 (0.001)	-0.001 (0.001)	-0.001** (0.001)	0.001 (0.001)	-0.001 (0.002)	-0.002* (0.001)
pc_road (ln)				0.0002 (0.001)	0.0002 (0.001)	-0.001 (0.001)	-0.001 (0.002)	0.001 (0.002)	0.003 (0.003)
employment (ln)				0.001 (0.001)	0.001 (0.001)	0.00001 (0.001)	0.007* (0.004)	-0.0004 (0.003)	0.008*** (0.003)
herfindahl				-0.023*** (0.004)	-0.021*** (0.004)	-0.009** (0.004)	-0.064*** (0.019)	-0.036 (0.025)	-0.095*** (0.020)
Prefecture-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,088,611	1,088,611	787,904	787,904	359,459	59,985	183,717	184,743	184,743
R <sup>2</sup>	0.310	0.310	0.326	0.326	0.343	0.478	0.429	0.415	0.415
Adjusted R <sup>2</sup>	0.213	0.213	0.216	0.216	0.208	0.310	0.235	0.256	0.256
Residual Std. Error	0.146 (df=955,502)	0.146 (df=955,501)	0.160 (df=676,718)	0.160 (df=676,717)	0.110 (df=297,878)	0.123 (df=45,350)	0.186 (df=137,165)	0.205 (df=145,291)	0.205 (df=145,291)

All standard errors are robust standard errors clustered at prefecture level.  
 \*p < 0.1. \*\*p < 0.05. \*\*\*p < 0.01.

fundamental aspect to consider concerns the different relevance that technological knowledge has across different economic activities. In fact, knowledge can be more important in certain industries rather than others in order for firms to maintain competitiveness and profitability (e.g. Hill and Rothaermel, 2003). This heterogeneity on the role of knowledge across sectors is connected to the different pace of technological progress in different industries, which may differ substantially depending on the nature of the production process within specific sectors, the types of production factors employed in different activities, the industry cost of entry, etc. (Acs and Audretsch, 2003; Bartel and Sicherman, 1999; Rigby and Essletzbichler, 2006). Therefore, in this section we empirically consider the relationship between foreign MNEs and local industry entry within different knowledge contexts, that is, by subdividing industries characterized by high knowledge intensity (HKI) and low knowledge intensity (LKI), following Zhu et al. (2017). Table 3 presents the results of this exercise. The positive and significant coefficients of *MNE* in columns 1 and 2 suggest that MNEs' investment in a given industry is positively correlated with the entry of that industry in the local economy, regardless of the knowledge content of the sector. Nonetheless, the heterogeneous role of knowledge across sectors emerges in the case of *relMNE*, indicating that the opportunity of local diversification based on the related activities of foreign MNEs is concentrated in HKI industries (column 1). Thus, the opportunities associated with the presence of foreign MNEs in sectors related to the local industrial base characterize industries where knowledge plays a predominant role for local incumbent firms to stay competitive, as compared to those in sectors where knowledge is less critical.

Furthermore, the distinction based on the role of knowledge intensity also reveals that the role of foreign MNEs in favouring local industry entry is associated with highly specific contingencies (columns 3–10). Specifically, a process of unrelated diversification into relatively complex activities (i.e. leapfrogging) can be facilitated by MNEs in the case of high knowledge intensity activities, in terms of both MNEs operating in sectors already present in the local economy as well as in related sectors (column 3). Again, this pattern tends to be visible in high knowledge intensity activities as compared to sectors where the use of knowledge is less important. Similarly, the role of MNEs can also facilitate a local diversification process towards related and complex activities (i.e. elite trajectory), but this remains limited to the operations of MNEs in sectors that are present in the regional economy. Therefore, this could more easily be the case of locations already endowed with complex skills and competences (columns 7 and 8). Finally, a catching-up trajectory of diversification, whereby a local economy can build on pre-existing low-complexity capabilities to enter related industries, may be favoured by MNEs offering a related knowledge base but only in the case of activities with a certain degree of knowledge intensity (column 9). Overall, these results suggest that the relationship between the presence of foreign MNEs and local diversification is very fragmented when the knowledge content of different activities is accounted for. This signals that the typology of local industry structure in terms of the role of knowledge and the pace of technological change matter for intercepting the chances of diversification potentially introduced through the external linkages of foreign MNEs. Consequently, the resulting regional opportunities of developing new industry specializations tend to follow specific trajectories, among which leapfrogging to unrelated and more complex activities emerges as the most relevant scenario, as it associated with a wide role of foreign MNEs in an ample spectrum of high knowledge intensity sectors.

### **Robustness checks**

A potential caveat of our empirical setting could be that our measure of MNEs in related sectors (*relMNE*) may be capturing vertical linkages between MNEs and local incumbents, in line with the existing literature about the inter-industry spillover effect (Görg and Greenaway, 2004; Javorcik, 2004; Rojec and Knell, 2018). In order to check whether our prior results hold once we include vertical linkages in the empirical model, we construct two measures of inter-industry effects, namely:

**Table 3.** Industrial heterogeneity of MNE presence on industry entry.

		Dependent variable									
entry		entry_leap		entry_fall		entry_elite		entry_catch			
HKI	LKI	HKI	LKI	HKI	LKI	HKI	LKI	HKI	LKI	HKI	LKI
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MNE	0.069*** (0.012)	0.035*** (0.014)	0.053*** (0.015)	0.047* (0.027)	0.244 (0.232)	0.012 (0.023)	0.061*** (0.021)	0.091*** (0.023)	-0.018 (0.045)	0.015 (0.028)	
relMNE	0.244*** (0.069)	0.054 (0.094)	0.176*** (0.058)	0.133 (0.127)	0.229 (0.163)	0.151 (0.231)	0.275 (0.189)	-0.071 (0.205)	0.791*** (0.186)	0.117 (0.158)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,627	42,572	69,883	22,019	1286	2151	8244	9954	1214	8448	
R <sup>2</sup>	0.311	0.313	0.318	0.322	0.656	0.393	0.428	0.456	0.582	0.459	
Adjusted R <sup>2</sup>	0.203	0.200	0.202	0.177	0.471	0.154	0.200	0.242	0.335	0.304	
Residual Std. Error	0.119 (df=69,744)	0.155 (df=36,556)	0.096 (df=59,794)	0.122 (df=18,136)	0.083 (df=836)	0.153 (df=1543)	0.217 (df=5893)	0.189 (df=7141)	0.229 (df=763)	0.167 (df=6565)	

All standard errors are robust standard errors clustered at prefecture level.

\*p < 0.1. \*\*p < 0.05. \*\*\*p < 0.01.



forward and backward linkages (*fIMNE* and *bIMNE*), obtained by replacing the relatedness linkage in formula (7) with input-output data, taken from *China's Input-Output Table 2002* published by National Bureau of Statistics. Since the industry classes used in *China's Input-Output Table 2002* are mainly 3-digit level (vs the 4-digit level of ASIF), we equally divide the share of 3-digit industries to their subclass 4-digit industries. Table A1 present the results of our baseline specification augmented with forward and backward linkages of MNEs. Across specifications, findings suggest that the relationship between industry entry and foreign MNEs is not affected by concurrent vertical linkages.

In most of our specifications, the inclusion of prefecture-industry effects allows us to control for unobserved location-specific shocks affecting specific sectors. These may include, for instance, specific local policies aimed at favouring activities that are key to the local economy. Nonetheless, it is possible that both industries and prefectures are subject to unobserved shocks at any point in time. In order to capture these potential confounding effects, we extend our baseline empirical setting by including prefecture-year and industry-year fixed effects to control all the prefecture and industry trends that can specifically affect industry entry at the spatial or sectoral level during the sample period. For instance, these may include specific regional policy actions or national industrial policies that influence the formation of new activities across time. Results, presented in Table A2, are consistent with our previous findings in both the aggregate industry entry specification (column 1) as well as for the four diversification trajectories discussed above (columns 2–5).

Furthermore, on the one hand, we propose an alternative measurement of our dependent variable based on employment figures of domestic firms only when calculating RCA matrix and the variable *entry*. The estimates based on this alternative version of the dependent variable are presented in Table A3. On the other hand, we employ a stricter industry entry definition by increasing the location quotient threshold to 2 in formula (2). The results are presented in Table A4. The results in both tables remain consistent with the evidence produced above.

Moreover, to assure that the relationship between MNEs and industry entry is not sensitive to the level of engagement of foreign MNEs, we further include minority MNEs in our analysis by including firms with the percentage of non-domestic paid-in capital larger than 10%, rather than 50% as defined in the previous section. As shown in Table A5 the main findings still hold.

Finally, in this paper, we define the share of MNEs over the total number of firms in a region following Cortinovis et al. (2020). However, there is a large variation in size between firms. To address the potential bias introduced by firm size distribution, we further use the share of MNEs' output value and number of employment to calculate our variables of interest (*MNE*, *relMNE* and *nebMNE*). The results are presented in Table A6 and Table A7 in Supplemental Appendix A, which further consolidate our main findings.

## Concluding remarks

This article investigates the relationship between MNEs and industry entry at the prefecture level by originally linking the literature on MNEs with studies on regional diversification in economic geography. Therefore, we contribute to the current debate regarding the role of extra-regional linkages in shaping regional diversification pathways (e.g. Boschma, 2017), by specifically looking at a very stable typology of external connection, that is, foreign MNEs setting up activities in the domestic economy. Furthermore, we integrate this perspective with the case of an emerging economy such as China by considering that, differently from the case of advanced economies, a path-breaking process of diversification (i.e. developing more complex and unrelated activities) might be a more plausible strategy to follow in these specific economic settings. This is motivated by the emerging economies' relative lack of local resources to generate sustained processes of diversification and their necessity to acquire capabilities in a diverse set of industry specializations. In this sense, establishing external linkages through foreign MNEs can be a viable option for emerging countries to encourage local diversification.

A long-standing literature, in this respect, considers MNEs as carriers of technical, organization and managerial knowledge that is hardly available locally and that can be accessed by local incumbents through a plethora of mechanisms (e.g. Caves, 1974; Chung, 2001; Javorcik, 2004; Rojec and Knell, 2018). Hence, the presence of foreign MNEs within a local economy can potentially stimulate a process of territorial diversification of economic activity based on the integration and recombination of the local and the foreign knowledge bases. We study this interplay for 279 Chinese prefectures by analysing a panel dataset containing all Chinese above-scale manufacturing firms, for the period 1998–2007. Our results suggest that the presence of foreign MNEs in the same industry and related industries is positively and significantly associated with a higher probability of industry entry at the local level. This association also holds for the entry of unrelated and complex industries. Furthermore, the effect of MNEs is larger for knowledge-intensive industries.

From the perspective of political economy, the unrelated and complex regional diversification in China could also be interpreted by the role of government. As a highly centralized authoritarian regime (Wahman et al., 2013; Wu, 2005), the local officials of Chinese cities are mainly appointed by the higher-level Party Committees. After the reform and opening up in the late 1970s, the legitimacy of the communist government was mainly based on economic development (Zhu, 2011). Due to the GDP-oriented performance appraisal mechanism of the Chinese official promotion system, local officials of different regions compete fiercely with each other to win in the promotion tournament (Cheung, 2009; Qian and Xu, 1993; Zhou, 2007), or more concisely, a regionally decentralized authoritarian system (Xu, 2011). To cater for the industrial policies outlined in the Five-Year Plans of national economic and social development made by the central government, local governments in particular tend to support the development of high-tech industries indicated by the Five-Year Plans, without much consideration of the local existing capabilities (Huang et al., 2015). More importantly, due to the land finance (Liu et al., 2022) and soft budget constraint (Kornai, 1992), local governments also have the power and financial resources to design preferential policies to attract advanced MNEs to achieve the industrial development goals (Qin, 2015). This could induce regional unrelated and complex diversification even when regions lack the appropriate knowledge base and capabilities. However, on the one hand, this government-led industrial strategy may be unsustainable if regions could not cultivate their own endogenous capabilities in this process. Without preferential policies, MNEs would probably flow to other regions and this would lead to a dramatic shrinkage of regional industries. On the other hand, there is a serious risk of duplication and homogenization in unrelated industrial diversification for regions, since they are all following the Five-Year Plans made by the central government and may jump in the same direction (Boschma, 2021a, 2021b).

This paper is not without limitations. For instance, the presence of foreign MNEs is not random across space but it may be endogenous to the local industry mix. To alleviate this, we have controlled for a comprehensive set of covariates and prefecture-industry fixed effects. Furthermore, all independent variables are temporally lagged. Nonetheless, our estimates should be carefully interpreted as statistical associations rather than causal effects. Another limitation of this paper lies in that our sample period was probably the most globally-engaging period of China's economic development in the post-Mao era. However, though nowadays some MNEs are exuding China due to various reasons, including the increasing cost of productive factors (Athukorala and Kohpaiboon, 2014), China–United States trade war (Wei, 2019) and Covid-19 shock (Barua, 2020), China is still the second largest FDI host country in the world with a 5% increase in 2022 (United Nations Conference on Trade and Development, 2023). The impact of foreign MNEs on China's regional diversification is still worth in-depth investigation. Due to data availability, we do not investigate the impact of MNEs' withdrawal on China's regional diversification. Future research could explore whether the outflow of foreign MNEs could lead to the downgrading of local industries in Chinese regions. This could to some extent test our findings from the opposite direction.

From the standpoint of policy, for both developed and lagging regions within emerging economies, the presence of foreign MNEs matter as an external source of industrial diversification. Thus, in order to enhance their industrial dynamism and minimize the risk of technological and industrial lock-in, regions should design targeted policies to attract foreign MNEs (Girma and Gong, 2008; Yao, 2006). This may be especially relevant for lagging regions, as their opportunities to access new trajectories of industrial development are less reliant on internal resources and the influx of external inputs may be fundamental. This paper, nonetheless, does not explore the composition effects related to the presence of MNEs, thus, we cannot account for potential detrimental influences of MNEs on the local industrial structure in terms of crowding out due to competition effects (Aitken and Harrison, 1999; Ascani and Gagliardi, 2020), which might be more severe in disadvantaged areas.

### Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

### Funding

The author disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Andrea Ascani gratefully acknowledges funding from the NWO-Innovational Research Incentives Scheme Veni SSH 2018 (Grant N. 016.Veni.195.085). Yibo Qiao acknowledges financial support from the China Postdoctoral Science Foundation(No.2023M741630) and National Natural Science Foundation of China (No.52378059, No.52278066).

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### Supplemental material

Supplemental material for this article is available online.

### Note

1. We limit our analysis to the period 1998–2007 because of data consistency. Indeed, the information about the composition of paid-in capital, which is needed to identify multinational firms, is absent during the period 2008–2010. Moreover, since 2011 the survey only includes firms with more than 20 million Yuan.

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