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Papers in Evolutionary Economic Geography

24.15

Utrecht University Human Geography and Planning

MNE Spillovers and Local Export Dynamics in China: The Role of Relatedness and Forward-Backward Linkages

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Abstract: This article investigates how MNEs influence the export behavior of domestic firms in the context of China. We conceptually disentangle different MNE spillovers related to local export dynamics, linking in a unique framework specific spillover mechanisms, channels, activation conditions and type of knowledge conveyed. Empirically, our analysis relies on a panel dataset containing all Chinese manufacturing firms in the period 2000-2007. The results show that *relatedness* linkages matter in the context of export quantity, while forward-backward linkages matter for the sophistication of export. These findings suggest that *relatedness* linkages convey mainly marketing-related knowledge spillovers, while forward-backward linkages are diffusing mainly product-related knowledge spillovers.

Keywords: Relatedness, forward-backward linkages, multinational enterprises, export, innovation, China

Introduction

The fast economic growth experienced by the Chinese economy is probably one of the most remarkable economic phenomena in the last forty years. Multiple factors have played a role in this outstanding performance, and among them two stand out: foreign direct investment (FDI) and export. They have both represented important sources of capital, technology and knowledge for Chinese firms (Autor et al., 2016; Mayneris & Poncet, 2015; Feenstra & Wei, 2010; Tingvall & Ljungvall, 2012).

Conceptually, scholars in international business and economics have long theorized a role of multinational enterprises (MNEs)[1] in fostering the export capabilities of domestic firms (Gorg & Greenaway, 2004; Aitken et al., 1997). Various studies provide convincing evidence on the relation between foreign MNEs' spillovers and domestic export activity (Greenaway et al., 2004; Kneller & Pisu 2007). In the case of China, Mayneris & Poncet (2015), Chen et al. (2013), and Swenson (2008) indicate that foreign multinationals provided crucial information for domestic Chinese firms to engage in export activities. Other scholars, such as Bloningen & Ma (in Feenstra & Wei, 2010), instead find the production activities of foreign MNEs in China accounted for a substantial share of Chinese exports, suggesting a more limited role for spillovers. At least to some the extent, however the presence of foreign firms seems to provide information and relevant knowledge for product upgrading and foreign market penetration through both intra-industry and inter-industry externalities (Kneller & Pisu, 2007; Chen et al., 2013).

In this paper, we theoretically disentangle and empirically test how exports of Chinese firms benefited from foreign MNEs' externalities within the same industry as well as across value-chains and from related industries. Specifically, our analysis studies the relation between spillovers from foreign firms on exports of Chinese firms (both "purely" domestic and domestic firms with investments abroad). Our attention is initially devoted to taking stock of the literature and develop a framework for understanding MNE export spillovers. Our theoretical arguments are based on insights on the product-specific nature of MNE export spillovers (Mayneris & Poncet, 2015; Koenig et al., 2010; Krautheim, 2012), the role of information on foreign markets for exporters (Artopoulos et al., 2013; Feenstra & Hanson, 2004) and the burgeoning literature on relatedness (Hidalgo et al., 2007, 2018, 2021). In combining these literatures, we highlight the role of industrial relatedness as a possible spillover channel (Lo Turco & Maggioni, 2019; Cortinovis et al. 2020; Howell 2020) and theoretically link spillover channels to different type of knowledge (Blyde et al., 2004; Kneller & Pisu, 2007).

Building on this framework, our empirical efforts focus on the channels through which foreign

[1] Our analysis relies on firm-level raw data, implying that we are not able to study FDIs specifically but rather the foreign firms performing those investments.

multinationals generate export-related knowledge spillovers to domestic firms and in turn influence the quantity and sophistication of domestic firms' exports. We argue that this approach allows us to capture the role of knowledge spillovers, differentiating between marketing practices (e.g., learning how to export and enter new markets), product practices (e.g., product upgrading) and process practices (e.g., changes in production techniques). For our analysis we use data for 331 Chinese prefectures with a panel dataset containing all Chinese manufacturing firms with sales above 5 million Yuan, in the period from 2000 to 2007. The results show that relatedness linkages matter in the context of export quantity, while forward linkages matter for the sophistication of exported products. The coefficients for intra-industry spillovers are instead negatively associated to export quantity. We interpret these findings as consistent with our conceptual framework and we suggest that relatedness-mediated spillovers are important mainly for marketing-related knowledge (e.g. importing and distribution networks abroad), externalities through forward linkages are associated to production-practices knowledge (e.g. production techniques relevant for product upgrading), while the presence of foreign MNEs within the same industry tends to hinder the export volume of domestic firms (Feenstra & Wei, 2010), possibly because of competition effects (e.g. multinationals better safe guarding critical information and knowledge assets).

The contribution of this paper is threefold. First, we integrate various strands of the literature to enhance our understanding and conceptualization of export spillovers from foreign firms. Second, we add to the literature on MNE spillovers, showing that relatedness is an important channel for knowledge diffusion, at least in the specific case of export-facilitating foreign MNEs' spillovers. In doing so, we bridge and leverage existing contributions in the literature to shed some light on possible mechanisms behind relatedness-mediated spillovers. Third, we theorize and empirically show that, among cross-industry channels of MNE externalities, relatedness and vertical linkages are likely to convey different sorts of export-relevant knowledge to domestic firms (Blyde et al., 2004; Kneller & Pisu, 2007). To the extent that marketing information for a specific product may be relevant also for related products (e.g. reliable importers, logistics), foreign multinationals in related industries may represent a crucial source of information for domestic exporters, especially as intra-industry knowledge spillovers are limited and foreign competition hinder export volume (Feenstra & Wei, 2010). Differently, spillovers through vertical linkages are more likely to convey insights on production processes, especially relevant for product upgrading and sophistication (Javorcik, 2004; Javorcik, et al., 2018). To the best of our knowledge, the type of knowledge conveyed across different channels for spillovers has only been marginally explored in the literature (Blyde et al., 2004; Kneller & Pisu, 2007).

The paper is organized as follows. The next section presents the literature review and develops our theoretical arguments in a coherent framework. The third section exhibits the data sources, methodology and modelling framework. The fourth section shows the results of regression analysis and robustness checks. The last section concludes.

Literature Review

MNE spillovers and domestic export

Multinational firms are characterized by being more productive, knowledge- and capital intensive than domestic firms (Navaretti & Venables, 2004). As a result, the extant literature on spillovers from foreign MNEs has mostly focused on externalities enhancing the productivity of domestic firms (Javorcik, 2004; Rojec & Knell, 2018). In addition to their greater productivity and knowledge capabilities, MNEs tend to have significant experience in organising foreign production and engaging in international trade. For this reason, a related stream of studies considers possible MNE spillovers facilitating local export activities (Aitken et al., 1997; Kneller & Pisu, 2007; Villar et al., 2020). We follow this stream of literature and try to conceptually dissect export spillovers from MNEs. To this aim, we focus on five key dimensions which can be helpful in clarifying how these externalities play out and impact domestic firms. The five dimensions and the articulation of MNE export spillovers are summarised in Table 1.

The first dimension refers to the specific mechanisms through which foreign firms generate externalities potentially beneficial for domestic companies (first column). Based on the literature on MNE spillovers, we indicate four possible *mechanisms* through which MNEs stimulate domestic export activities: competitive pressure, demonstration/imitation effects, information spillovers and labour mobility (Gorg & Greenaway, 2004; Greenaway et al., 2004; Kneller & Pisu, 2007). The second dimension focuses on the *medium* through which a specific mechanism unfolds. Deepening the frequently used distinction between intra-industry and inter-industry spillover effects of multinationals, we suggest four distinct channels for spillover effects (see the second column of Table 1). Along with within-industry or horizontal spillovers and inter-industry effects, typically split in backward and forward linkages, we incorporate a recently theorized relatedness-mediated channel (Cortinovis et al. 2020; Lo Turco & Maggioni 2019). The third dimension pertains the *activation* of the spillover mechanisms and channels, which we link to the specific incentives MNEs and domestic firms face (third column). In line with the extant literature, we consider that a mechanism may be either activated or obstructed by the foreign or domestic firm, based on the expected effect (e.g. knowledge leakage) (Navaretti & Venables 2004). The fourth dimension considers if and what *type of knowledge* may be conveyed through a certain mechanism in a given channel. This aspect has been only marginally considered in the MNE export spillover literature, and thus represents an important innovation (fourth column in Table 1). As argued more in detail below, we follow Artopoulos et al. (2013) and consider three main types of knowledge that can be conveyed by export externalities: knowledge about products (e.g. design specifications), about production processes (e.g. production technologies) or about marketing practices (e.g. specific requirements for the product to enter a market). The last dimension (fifth column of Table 1) focuses on the possible *impact on exports* that the MNE-generated spillovers may have. While the impact of MNE export externalities may be various, we theorize two main possible impacts: one on the quantity of export (either in terms of quantity of good exported or destinations which are entered) and the other on the sophistication of export.

Before discussing the framework emerging from Table 1, it is important to clarify and connect to the literature the dimensions of our framework.

The mechanisms of MNE export spillovers

Similar to the case of productivity-enhancing spillovers (Gorg & Greenaway, 2004; Javorcik, 2008), competitive pressure, exposure to knowledge about technology and management practises through demonstration/imitation, information externalities (e.g. product compliance and regulation) and acquisition of human capital thanks to labour mobility make domestic firms better able to engage in export activities (Gorg & Greenaway, 2004; Kneller and Pisu, 2007; Javorcik 2015). These four mechanisms are reported in the first column of Table 1.

Starting with competition externalities, these effects do not convey knowledge but can nonetheless impact on the ability of local firms to engage in export activities by pushing domestic firms to reduce X-inefficiency and fostering the adoption of new technologies or otherwise exit the market (Gorg & Greenaway, 2004; Navaretti & Venables, 2004; Resmini 2019). Importantly, the effects of this mechanism materialize when both domestic and foreign firms operate in the same industry and are therefore direct competitors. Because the consequences of competitive pressure from MNEs may be reflected on both productivity and innovation, in our framework this mechanism impacts both the quantity and the sophistication of domestic exports.

Imitation and demonstration effects represent a crucial mechanism explaining how domestic firms can acquire and make use of knowledge brought in by foreign companies. Whether the externalities materialize through imitation, which highlights the role of copying successful routines and products of MNES, or through demonstration, which instead suggests a more active role for MNEs in showing their routines and assets, the common factor is the transfer of knowledge between foreign firm and domestic firm (Navaretti & Venables, 2004; Javorcik 2015). As discussed in the next section, the type of knowledge transferred and the impact it has depends on the channel through which the spillovers occur.

With respect to information spillovers, MNEs represent a source of information and experience on international markets. Considering the crucial role of uncertainty and information asymmetries in shaping both import and export flows (Rauch & Casella, 2003; Feenstra & Hanson, 2004) and the sunk costs that domestic firms need to face in order to export (Robert and Tybout, 1997), information spillovers from other exporters – such as multinationals – can help reducing the costs of exports by tapping in informational networks (Gorg & Greenaway, 2004; Kneller and Pisu, 2007; Krautheim, 2012). In this respect, foreign firms are likely to represent a source of potentially critical information for domestic firms with respect to distribution networks, regulatory frameworks of exporting destinations and other organizational aspects of exporting (Kaminsky & Smarzinka, 2001; Lesher & Miroudot, 2008; Kneller and Pisu, 2007). Given these types of information are relatively specific to the product at stake, our framework suggests information spillovers are likely to diffuse within industries and across related industries, with other channels playing only a minor role in information spillovers.

Arguably, the most important channel, both for MNE externalities in general and specifically for export MNE externalities, pertains the acquisition of human capital, typically through labour mobility from foreign to domestic firms. We expect access to human capital through this mechanism to influence export activities in two main ways. First, former MNE employees can make the domestic firms more productive and innovative which could be reflected in better export performances. Secondly, the experience and social connections abroad of former MNE employees may be crucial for reducing the costs and facilitating export activities of local firms. Recent evidence at individual level shows that export and import experience of managers is critical to engage in international trade (Mion et al., 2016; Bisztray et al., 2018). For instance, Mion and coauthors (2016) show that a firm with managers with specific export experience in terms of country and product is related to greater export performance of firms. In our framework, whether the impact of labour mobility comes through productivity and innovation side or through experience and social connection is associated to the channel and the type of knowledge at stake.

The channels of MNE export spillovers and their activation

The second dimension of our framework focuses on the channels through which MNE export spillovers diffuse. Typically, the literature on MNE spillovers envisages three channels embedded in the industry in which a foreign firm is active. Specifically, the three channels are: within the same industry (or horizontal spillovers), across upstream value-chain relations (backward linkages, where the MNE is downstream and the domestic firm is upstream) and across downstream value-chain relations (MNE upstream and domestic counterpart downstream). Whereas these channels are clearly motivated by market relations (e.g. within industry competition, mutual dependency between buyer and supplier), some scholars have argued that additional channels may be present (Branstetter 2001; Cortinovis et al. 2020; Howell 2020). In our framework, the fourth channel we propose builds on the economic geography literature on relatedness (Hidalgo et al., 2007; Boschma

& Capone, 2015). In this literature, relatedness between two products (or industries, or technologies) refers to the similarity and complementarity of capabilities used to produce them. When two products require the same or similar capabilities, firms can more easily diversify from one to the other (Hidalgo et al., 2007, 2018). In the same way, when relatedness between two industries is high, it is easier for firms in one industry to use and recombine knowledge, capabilities and inputs from the other industry (Cortinovis et al., 2017, 2020). In the case of MNE spillovers, the underlying assumption is that the more two industries are related, the easier it is for firms in one industry to learn and benefit from firms in another industry. In this sense, relatedness can be thought as encompassing a wide set of features which make two industries similar/complementary one another, from inputs and human capital to production process and regulations (Hidalgo et al., 2007, 2018).

An important aspect to consider in relation to spillover channels is their activation. The literature on MNE externalities highlights how foreign firms are aware of the risk of domestic firms benefitting from their presence (Javorcik, 2015). For this reason, especially in the case of direct competitors, multinationals are likely to actively prevent, or at least limit, possible positive externalities. On the other hand, as value-chain connections create mutual interdependence between local and foreign firms, MNEs have the incentive to share technological knowledge with local partners (either upstream or downstream the value chain). This suggests, as reported in Table 1, that MNEs tend to obstruct spillovers through the horizontal channel, which domestic firms instead try to activate, while MNEs may enable spillovers when it comes to backward and forward linkages – at least when they do not imply local firms poaching MNE employees. In the case of relatedness-mediated spillovers, the activation of the channel mostly comes from the domestic firm interested in obtaining technological insights, information or to hire employees from MNEs. Differently from the horizontal channel, a MNE may not actively prevent the diffusion of externalities – with the possible exception of those coming from the human capital channel - given the domestic firm is not one of its direct competitors.

Knowledge types and the impacts of export spillovers

Intersecting spillover mechanisms, channels and their activation reveals how externalities play out differently depending on the specific circumstances identified by the first three dimensions we analysed so far. A further dimension to consider is whether any difference exists in terms of the type of knowledge disseminated through different mechanisms and channels.

Given the important role of uncertainty, information asymmetries and entrepôt economies in international trade (Rauch & Casella, 2003; Feenstra & Hanson, 2004), domestic producers need substantial information to successfully engage in export activities. In this respect, MNEs play an important role in spilling over information and knowledge to domestic firms (Lesher & Miroudot, 2008), with some scholars suggesting that export externalities from MNEs tend to convey the product- and destination-specific information (Mayneris & Poncet, 2015; Koenig et al., 2010; Harasztosi, 2016). As the same time, only few contributions studying MNE export spillovers and these provide very limited theorisation on the relation between type of knowledge and spillover channels. Blyde et al. (2004), followed by Kneller & Pisu (2007), are the only ones building a convincing theoretical argument for intra- and inter-industry spillovers diffusing different types of know-how. According to them, intra-industry spillovers could theoretically diffuse sector-specific knowledge but MNEs have a strong incentive to limit such knowledge spillovers to competitors. Differently, inter-industry spillovers spread generic insights, given the sector-specific knowledge would be hardly applicable along the value chain.

In our framework, we combine the intuition of Blyde et al. (2004) and Kneller & Pisu (2007) with the insights from the micro-economic literature on trade, especially from emerging economies (Iacovone et al. 2010; Mayneris and Poncet 2015; Elango and Pattnaik, 2007; Artopoulos et al. 2013). This latter strand of literature shows that, to be successful, exporters from developing countries need to adopt new set of business practices, different and complementary to those prevailing in the domestic market (Iacovone & Javorcik 2010; Mayneris & Poncet 2015). Artopoulos et al. (2013) analyses in detail these different practises and categorized them in three groups: product practices, production practices, and marketing practices. Product practices refer to the knowledge necessary to identify the special demand of specific products in the foreign markets, arising from higher requirements for quality, functional sophistication, or demand idiosyncrasies. These practises are therefore very specific to the product and likely to be held by firms engaging exactly in the same activity, such as foreign firms in the same industry. Production practices instead relate to the actual routines and processes for producing specific goods of higher quality. Achieving these improvements often requires significantly changing the production processes, in terms of machinery, tasks and operations carried out by workers and input obtained by suppliers (Artopoulos et al. 2013). Crucial sources of insights and knowledge on production processes are foreign buyers and suppliers. For instance, Javorcik (2004) reports the buyer-supplier relations with a foreign firm allowed its supplier, a Czech producer of aluminium alloy, to improve its quality control system and reduce the number of defective items produced. Lastly, marketing practices concern how products are marketed and sold in the exporting destinations and range from business conducts, advertising, and packaging choices to the ability to find and use reliable distributors abroad (Artopoulos et al. 2013). Also in this case, the marketing knowledge required for a domestic firm to successfully export is relatively product specific (Blyde et al. 2007; Mayneris & Poncet 2015), suggesting the horizontal and relatedness channels being the main sources of externalities conveying marketing practises.

The fact that different types of knowledge are conveyed by different mechanisms and different channels suggests that, depending on the specific situation, the impact of these MNE externalities may vary. For sake of simplicity, in our framework we focus on two loosely defined types of impact: the impact on quantity of exports and the impact on the sophistication of the exported good. The first type (quantity) captures both the extensive (starting to export or not) and intensive margins (how much is exported) of export, as well as market penetration (how many countries). The second dimension considers the quality or sophistication of the exports (how complex a certain product is). While a simplistic, our framework allows to intuitively link knowledge types and impacts. Specifically, we assume that knowledge related to either product or production may especially result in improvement in the sophistication of exports (Javorcik et al. 2018), since the local firm would become aware of new functions, designs, inputs or technologies to produce a certain good. Clearly, this may, in a second stage, also result in an increase in the quantity of exports and destinations in line with a "start small" export model (Iacovone & Javorcik 2010). In the case of marketing practises, we expect the impact of spillovers conveying such type of insights to concentrate on the quantity of exports. Using more reliable distributors or investing in advertising and marketing processes does not affect the actual sophistication of the exported good but it likely increases its appeal to foreign consumers (Mion et al. 2016; Artopoulos et al. 2013; Javorcik 2015).

Taking stock: a comprehensive framework for MNE export spillovers

Combining the five dimensions discussed above in a single framework allows us to bring some clarity and provide a systematic overview of export spillovers from MNEs. Table 1 below takes stock of our discussion and review of the literature to formalize our expectations in terms of the impact of export spillovers from foreign MNEs. We discuss Table 1 summarizing our arguments by spillover channels.

Based on our arguments, we expect foreign MNEs' spillovers within the same industry to potentially cover both product, production and marketing practices (Artopoulos et al., 2013) and impact on both the quantity and the sophistication of domestic exports. The four main mechanisms at play are the competition, imitation/demonstration, information spillovers and human capital ones. The competition mechanism – unique to this spillover channel - is activated automatically once an MNE enters the local industry while the other three are led by the action of domestic firms, with typically some obstruction by the multinationals to prevent knowledge leakages to competitors (Görg & Greenaway, 2004; Rojec & Knell, 2018).

Vertical linkages (backward and forward) diffuse externalities derived from imitation/demonstration effects and through human capital/labour mobility (Gorg & Greenaway, 2004; Kneller & Pisu, 2007; Javorcik 2004). The activation of the two mechanisms will occur either by MNEs, especially in the case of demonstration effects, or by local firms, in case of spillovers related to human capital acquisition. In either case, we expect the type of knowledge to be mostly focused on production practices and thus having an impact on the sophistication of domestic exports (Javorcik 2004; Javorcik et al. 2018). The upgrading of products or processes may still allow the domestic firm to be more competitive in foreign markets and achieve a better export performance (in terms of number of exporting firms and/or quantity of export), but only as a second order effect.

Lastly, relatedness channel is linked to three mechanisms: imitation/demonstration, information spillovers and human capital/labour mobility. These mechanisms are mostly activated by domestic firms, leveraging the lack of direct competition and the similarity/complementarity of capabilities across related industries (Hidalgo et al., 2007, 2018). The types of knowledge diffused by these mechanisms through the relatedness channel is expected to concern primarily product and marketing practices. As a result, we expect possible relatedness-mediated export spillovers to increase the quantity of export of domestic firms rather than impacting their sophistication.

Table 1 The knowledge spillover channels from foreign MNEs to domestic firms

Spillover mechanism	*Spillover channel*	*Activation*	*Knowledge type*	*Impacts on export*
Competition	Horizontal	Automatic/MNE-activated	-	Export quantity (through productivity improvements) Export sophistication (through innovation)
Imitation/demonstration effects	Horizontal	domestic- activated, obstructed by MNEs	Product, production, and marketing practices	-
	Backward	MNE- activated	Production practices	Export sophistication
	Forward	MNE- activated	Production practices	Export sophistication
	Relatedness	domestic- activated	Product and marketing practices	Export quantity
Information spillovers	Horizontal	domestic- activated, obstructed by MNEs	Marketing practices	-
	Relatedness	domestic- activated	Marketing practices	Export quantity
Human capital/labour mobility	Horizontal	domestic- activated	Product, production, and marketing practices	Export quantity and sophistication
	Backward	domestic- activated	Production practices	Export sophistication
	Forward	domestic- activated	Production practices	Export sophistication
	Relatedness	domestic- activated	Product and marketing practices	Export quantity

Data, Variable, and Model

Data

For the empirical analysis, we rely on the following sources of data: the *Annual Survey of Industrial Firms 1998-2013* (ASIFs for short) and the *China Customs Import & Export Trade Data 2000-2016* (CCIETD for short). We identify MNEs from the former and obtain information of export from the latter. ASIFs is provided by National Statistical Bureau of China and include rich information on firms, such as location, 4-digit industry code, number of employees, total output value. This data is limited to firms with sales above 5 million Yuan in three categories of industries: mining, manufacturing, and electricity, gas, and water production. Following He et al. (2018), we focus on manufacturing firms since they have more freedom in selecting locations than the other two industries, which rely heavily on natural resources. We limit our analysis to the period to 2000-2007 due to three reasons. First, the information about the composition of paid-in capital is absent during 2008-2010, which we mainly rely on to identify multinational firms. Second, in 2011, the coverage of survey firms is narrowed to those with more than 20 million Yuan in sales from 5 million used before. Last, CCIETD dataset only contains information after 2000.

During our sample period, the classifications of industries in 1998-2002 and 2003-2007 are different, since the former is codified in accordance with the *Industrial classification for national economic activities (GB/T4754-94)*, while the latter is according to *Industrial classification for national economic activities (GB/T 4754-2002).* In order to unify them, we follow the strategy by Brandt et al. (2012) and make use of their concordance table to merge the different industry codes between two periods. Following standard practices (Chen, 2018), observations which violate the common sense of accounting are dropped, that is, observations with negative number of employees, industrial output or new product output and those total paid-in capital does not equal the sum of its subcategories. Information on export product codes, export value, and export destination of domestic firms come from Economy Prediction System (EPS), one of the largest and most comprehensive data suppliers of China study. EPS provides the matched dataset between ASIFs and CCIETD. During our sample period, the matching rate between ASIFs and CCIETD varies between16.06% and 23.05%. The export value is deflated by the CPI inflation rate from U.S. Bureau of Labor Statistics with 2000 as the base year. Based on the ASIFs database, we constructed an industry-prefecture panel dataset for 423 four-digit manufacturing industries in 331 prefectures during our sample period.

Variable construction

Dependent variables

We focus on the impact of foreign MNEs' spillovers on domestic firms' export quantity and sophistication. On the one hand, based on the information on export value, we compute the total export value of domestic firms (*domexp*) and the total number of domestic firms with exporting activities (*domnum*), for all prefecture-industry observations at every year. Based on the information on export destination, we build a variable that measures whether a prefecture-industry (only including domestic firms) exports to new markets (*dommar*). The value of *dommar* is set to 1 if a prefecture-industry exports to countries which are not in domestic firms' exporting country list in the previous two years but are in the exporting country list of all MNEs in the prefecture in the previous two years, otherwise 0.

On the other hand, we calculate the sophistication of export using the weighted average complexity index of domestic firms' exporting products in industry i, in prefecture r, at year t, $dompci_{i,r,t}$. As shown in equation (1), $S_{p,i,r,t}$ is the share of product p in total export of all the domestic firms in industry i, in prefecture r, in year t, and PCI_p is the complexity of product p. We make use of the complexity index in *The Atlas of Economic Complexity*, which is provided by Harvard's Growth Lab led by Ricardo Hausmann, to calculate the complexity of industries in our sample, which results in a weighted average complexity of exporting products. The complexity of products is calculated with international trade data with the method proposed by Hidalgo & Hausmann (2009). To guarantee the exogeneity and stability of the complexity measure, we take the average of the products complexity in the last three years (that is 1997-1999) before our sample period 2000-2007. In Table A1 in the Appendix A, we show the top and last 10 most complex industries defined by the average complexity of products from domestic firms.

$$dompci_{i,r,t} = \sum_{p\in i} S_{p,i,r,t} * PCI_p \tag{1}$$

Key explanatory variables

Our key variables of interest measure in different ways the presence of MNEs in a prefecture. The first variable, i.e., *MNE,* measures the share of MNEs (on the total number of firms) in each prefecture-industry. Similarly, *relMNE* represents the presence of MNEs in related industries, and *flMNE* and *blMNE* measure the presence of MNEs in forward and backward industries respectively. In order to identify MNEs, we compute the share of non-domestic paid-in capital from foreign countries and regions (including Hongkong, Macau and Taiwan) for all firms. A firm is regarded as an MNE if its share of non-domestic paid-in capital is higher than 50%[2], since in this case the

[2] In undocumented robustness checks (available upon request) we show our findings are robust when defining multinationals based on a 10% foreign ownership share. This threshold is derived from the publication *Several Opinions Related to Foreign Investment in Listed Companies* issued by the China Securities Regulatory Commission (CSRC) in 2001, according to which the shares of the listed company are considered to have a foreign investment component only if the proportion of foreign shares in the total share capital is higher than 10%. Although not all of our sample firms are listed companies, we argue that this is still an appropriate definition to identify minority MNEs in our case.

foreign economic entity is de jure able to control the decision making in the company (Dunning & Lundan, 2008; Elekes et al., 2019).

To calculate the variable *relMNE*, we first need to obtain the relatedness between pairwise industries. To this aim, we rely on the concept and method proposed by Hidalgo et al. (2007) to measure the proximity (relatedness) between different industries, the idea behind which is that industries frequently co-occurring require similar technologies, knowledge, capital, institutions and skills and are therefore related. To calculate relatedness between each pair of industry, we first define the industries in which every prefecture is specialised in formulas (2) and (3), following Hidalgo et al. (2007). An industry *i* in prefecture *r* in year *t* is regarded to have a specialization or revealed comparative advantage ($RCA_{i,r,t}$=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 ratio between the share of employment of industry *i* in year *t* against the prefecture's total employment, and the share of employment of industry *i* across all prefectures in year *t* is larger than 1. In a more formal way:

$$LQ_{i,r,t} = \frac{E_{i,r,t}}{\sum_i E_{i,r,t}} \Bigg/ \frac{\sum_r E_{i,r,t}}{\sum_{i,r} E_{i,r,t}} \tag{2}$$

and

$$RCA_{i,r,t} = \begin{cases} 1, if\ LQ_{i,r,t} > 1 \\ 0, otherwise \end{cases} \tag{3}$$

Then the relatedness between any two industries *i* and *j* in year *t* is the minimum value 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* (as shown in formula (4)). In Figure B1 in Appendix B, we present the hierarchically clustered relatedness heatmap between sample industries in 2001/2003/2005/2007. The distribution pattern shows that high values (brighter color) are mainly along the diagonal, indicating some industries highly related with each other and unrelated with the rest ones, which is also consistent with of Hidalgo et al. (2007).

$$relatedness_{i,j,t} = min\{P(RCA_{i,t} = 1 | RCA_{j,t} = 1), P(RCA_{j,t} = 1 | RCA_{i,t} = 1)\} \tag{4}$$

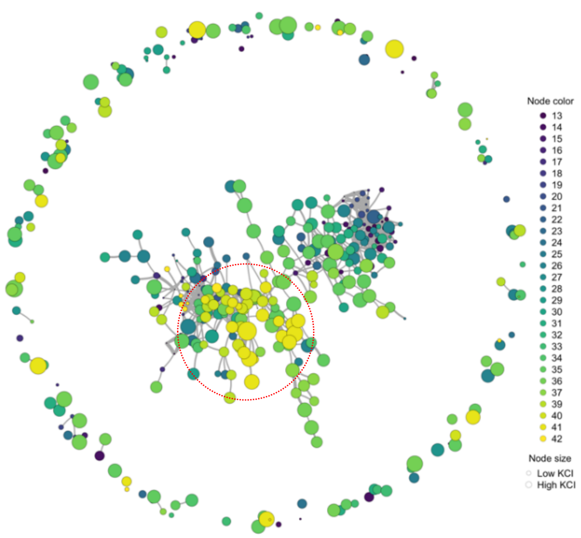
The result of equation (4) is a N × N symmetric relatedness matrix with its elements as the relatedness score between pairwise industries, and its main diagonal is set to zero. We then construct our variable of interest, $relMNE$, by summing up the relatedness-weighted shares of MNEs (the defined variable *MNE*) in the related industries. Specifically, the variable $MNE_{j,r,t}$ indicates the share of MNEs in the related industry *j* of the focal industry *i*, in prefecture *r* in year *t*. Following the idea of relatedness density (Hidalgo et al., 2007), we only consider the related industries with an RCA, which are relatively large in size and have developed capabilities to spill over to other industries. This is summarised in equation (5).

$$relMNE_{i,r,t} = \sum_{j \neq i} relatedness_{i,j,t} * (MNE_{j,r,t} * RCA_{j,r,t}) \quad (5)$$

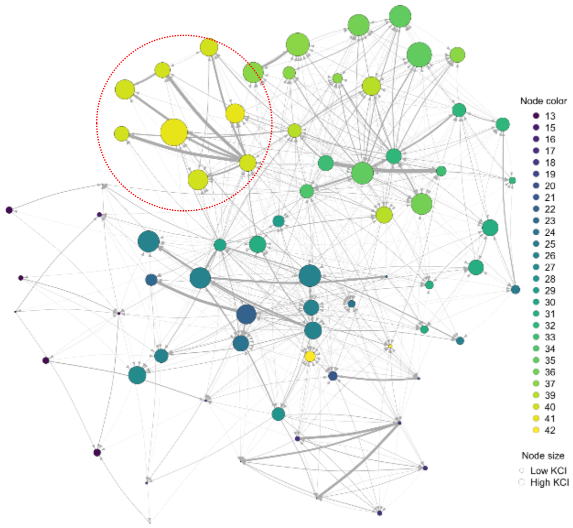
As shown in formula (6), the variable $flMNE$ ($blMNE$) is achieved by replacing the relatedness between industries with forward (backward) linkages in equation (5). The *fl* and *bl* are the forward and backward linkages between industries respectively, which are calculated with *China's Input-Output 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, which is higher than the 4-digit level in ASIF, we equally divide the share of 3-digit industries to their subclass 4-digit industries.

$$flMNE_{i,r,t}[blMNE_{i,r,t}] = \sum_{j \neq i} fl_{i,j}[bl_{i,j}] * (MNE_{j,r,t} * RCA_{j,r,t}) \quad (6)$$

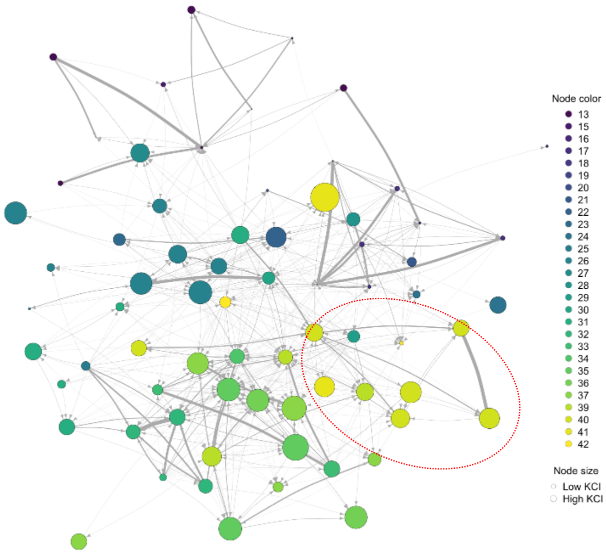
In Figure 1, we further present the network representation of relatedness, forward, and backward linkages among Chinese industries in 2007, where nodes represent industries, node size represents complexity of industries and links represent relatedness, forward or backward linkages between two nodes (industries) respectively. From the perspective of network structure, we can find that the main component in the network of related linkages includes a wide range of different industries (nodes with different colours), whereas, in the networks of forward-backward linkages it is mainly composed of the same industries (nodes with the same colours). This suggests that relatedness linkages are more widespread across industries and that forward-backward linkages are more restricted within supply chains. For example, the communication equipment, computer and other electronic equipment manufacturing industry (industry code 40) is densely interwoven with many other industries in the relatedness network, however, in the forward and backward networks, the strong linkages are more circumscribed in the same industry.



Relatedness linkages



Forward linkages



Backward linkages

Figure 1 Network representation of the relatedness, forward, and backward linkages of Chinese industries in 2007 (see the industry codes in Appendix B)

Control variables

Following the existing literature, we have also included a number of control variables. In our setting, there may be spatial spillovers from MNEs located in neighbouring prefectures, which could affect the relationship between MNE presence and exports of domestic firms (Cortinovis et al., 2020). Therefore, in order to control for these confounding factors, we include the variable nebMNE. It is operationalised as the share of MNEs in the focal industry in neighbouring prefectures, which are defined as those prefectures that share a common border with the focal prefecture. Specifically, the spatial weight matrix **W** is a K × K matrix with elements being 1 when two prefectures have a common border, and 0 otherwise, and K is the number of prefectures. **W** is row standardized and its main diagonal is set to zero.

$$nebMNE_{i,r,t} = \sum_{k \neq r} W_{r,k} * (MNE_{i,k,t} * RCA_{i,k,t}) \quad (7)$$

The literature suggests that exporting firms tend to be more productive and capital intensive (Greenaway et al., 2004). To control for these effects, we include two additional control variables: the output per worker (*productivity*, 1000 yuan per worker) and the capital per worker (*pccapital*, 1000 yuan per worker) at the prefecture-industry level. Moreover, since innovative regions tend to have higher capabilities in export activities (Sandu & Ciocanel, 2014), we also add the variable *rdinput*, which help to control for the impact of innovative inputs and capabilities at the prefecture level. This variable is measured by a prefecture R&D expenditure per capita (yuan per person). Size effects are controlled by including the variables *population* (10,000 people) and *pcgdp* (in yuan), which are proxies for prefecture population size and GDP per capita, respectively (Vijil & Wagner, 2012). Finally, to capture the impact of transport and logistics on exports, we include the level of infrastructure with the variable pcroad, which is defined as the road area (in square metres) per capita in a prefecture (Vijil & Wagner, 2012). All these five prefecture-level variables are taken from the *China City Statistical Yearbook 1999-2007* (for short, CCSY). Finally, we also control for the size of the industry in a prefecture by the number of firms in the industry in the prefecture (*firm*) (Greenaway et al., 2004).

Model and descriptive statistics

To explore the spillover channels from MNEs to domestic firms, we formulate the regression equation (8) as below.

$$\begin{aligned} y_{i,r,t} = {} & \beta_1 MNE_{i,r,t-1} + \beta_2 relMNE_{i,r,t-1} + \beta_3 flMNE_{i,r,t-1} + \beta_4 blMNE_{i,r,t-1} \\ & + \boldsymbol{\gamma X} + \alpha_{i,r} + \tau_t + \epsilon_{i,r,t} \end{aligned} \quad (8)$$

We use four kinds of dependent variables ($y_{i,r,t}$) in our analysis, the value of export, number of exporters, new export market entry, and sophistication of exporting products by domestic firms in industry *i*, in prefecture *r*, at year *t*. Variable $MNE_{i,r,t-1}$ represents the share of MNE number in industry *i*, in prefecture *r*, at year *t-1*. The variable $relMNE_{i,r,t-1}$ represents the weighted share of MNEs in the related industries of the focal industry *i*, in prefecture *r*, at year *t-1*. The variable $flMNE_{i,r,t-1}$ and $blMNE_{i,r,t-1}$ represent the weighted share of MNEs in the forward and backward industries of the focal industry *i*, in prefecture *r*, at year *t-1* respectively. In equation (8), $\boldsymbol{X}$ represent our set of control variables, as discussed in the previous section, variables *nebMNE*, *productivity*, *pccapital* and *firm* are at prefecture-industry level, whereas variables *rdinput*, *population*, *pcgdp* and *pcroad* are at prefecture level. Furthermore, our model also controls industry-prefecture ($\alpha_{i,r}$) and year (τ_t) fixed effects. All the independent variables are one-year lagged and standardized in the model. The standard errors are clustered at prefecture and 3-digit industry level to address the potential autocorrelation and heteroscedasticity in the error terms. We cluster standard errors at the industry level in the input-output table, which includes 71 3-digit manufacturing industries in total. Otherwise, the standard errors would be systematically downward biased (Moulton, 1990; Angrist & Pischke, 2008). The descriptive statistics and data source of our variables are presented in Table2, and Table A2 in Appendix A shows the correlation table of main variables. In Appendix C, we present additional descriptive statistics about the quantity and quality of regional export in China.

Table 2 The descriptive statistics of main variables

Variables	Source	No. of Observations	Min	Median	Max	Mean	Std. Dev
domexp (ln)	CCIETD	301365	0.000	0.000	22.675	2.814	5.650
Domnum	CCIETD	301365	0.000	0.000	154.000	0.507	2.679
dommar	CCIETD	230056	0.000	0.000	1.000	0.177	0.382
dompci	CCIETD, Atlas	61072	-2.293	0.260	2.572	0.114	0.911
MNE	ASIFs	299730	0.000	0.000	1.000	0.104	0.245
relMNE	ASIFs	299730	0.000	0.025	1.000	0.073	0.113
flMNE	ASIFs	299730	0.000	0.003	0.605	0.016	0.034
blMNE	ASIFs	299730	0.000	0.002	0.604	0.016	0.039
nebMNE	ASIFs	299730	0.000	0.000	1.000	0.029	0.082
productivity	ASIFs	283429	0.001	138.594	111838.587	223.604	529.534
pccapital	ASIFs	284874	0.006	129.532	335141.083	219.779	1255.559
rdinput	CCSY	270733	0.000	1.958	160.038	6.939	17.341
population	CCSY	270733	15.960	463.000	3198.870	523.774	355.072
pcgdp	CCSY	270733	1637.137	11273.454	295359.569	17685.807	22684.205
pcroad	CCSY	270733	0.140	6.500	64.000	7.696	5.453
firm	ASIFs	299730	1.000	2.000	1083.000	5.582	15.689

Regression Analysis

Baseline results

We first explore foreign MNEs' knowledge spillovers to domestic firms on export quantity. The results of the regression models are reported in Table 3. We add our variables of interest one by one, and all control variables are included. The results of models (1)-(4) show that the coefficient estimate of *relMNE* is positive and highly significant, while the coefficients of *flMNE* and *blMNE* are both insignificant, which is in line with our expectations: spillovers from MNEs in related industries boost export of domestic firms. The coefficient of *MNE* is instead negative and highly significant, which is also in line with our theoretical framework. We interpret this result in the light of possible competition effects: domestic firms experience a market share decline due to the competition of MNEs operating in the same sector (Feenstra & Wei, 2010). Overall, the above findings show that on the one side the presence of MNEs in *related* industries enhances the exporting quantity of domestic firms, on the other side the MNE presence in the *same* industry crowds-out domestic firms. In models (5) and (6), we further explore the role of MNEs in two other exporting activities: the number of domestic exporters and the new exporting market-entry. The results further confirm our expectations: while MNEs in related industries show a positive relation to the number of domestic exporters and entry in new markets, those in the same industry report negative coefficients, instead the estimates of the coefficients of forward-backward linkages are both insignificant. Overall, these results seem to indicate that relatedness linkages with MNEs tend to improve the export capabilities of Chinese firms, both in terms of export quantity, number of exporters, and new market entry of domestic firms.

In Table 4, we explore foreign MNEs' knowledge spillovers to domestic firms on export sophistication. The results in models (1) – (4) show that all variables of interest, but the one measuring vertical linkages (*flMNE*), are not significant. These findings support our theoretical expectations: vertical linkages represent a channel to diffuse prevalently product-related knowledge. Forward linkages with MNEs can enable domestic firms to get access to high-quality and less-costly inputs, thus helping them to climb the ladder of complexity and increase the sophistication of their export baskets.

Though we are not able to directly observe the spillovers of marketing related knowledge between MNEs and domestic firms, our findings are consistent with the ideas that different channels of MNEs spillovers convey different types of knowledge. Comparing results in Table 3 and 4 suggests that relatedness-mediated MNE spillovers diffuse information which is relevant to: a) increasing the volume of export; b) starting to export and in entering new markets (Table 3). However, they do not impact the level of sophistication of the export basket (not significant coefficient for relMNE in Table 4). In this sense, relatedness can be conceptually associated to marketing knowledge, which is highly relevant for the export performance of companies, but less for the design of products or for upgrading production processes. Differently, spillovers through forward-linkages are associated to export sophistication (Table 4), but not to better export performance in terms of quantity, number of exporters and new destinations (see the not significant coefficient for flMNE in Table 3). Given their impact on export complexity (Javorcik et al. 2018), value-chain relations linkages can then be thought of as channels for production-relevant knowledge spillovers.

Table 3 Foreign MNEs' spillover channels in export quantity

	Dependent variable:					
	domexp (ln)				*domnum*	*dommar*
	(1)	(2)	(3)	(4)	(5)	(6)
MNE	-0.314***	-0.335***	-0.319***	-0.336***	-0.144***	-0.011***

	(0.041)	(0.042)	(0.041)	(0.042)	(0.030)	(0.003)
relMNE		0.502***		0.482***	0.206*	0.019***
		(0.118)		(0.114)	(0.122)	(0.007)
flMNE			0.113	0.048	-0.013	0.003
			(0.072)	(0.074)	(0.060)	(0.005)
blMNE			0.048	-0.010	0.058	-0.002
			(0.059)	(0.056)	(0.070)	(0.004)
nebMNE	0.094***	0.070***	0.092***	0.071***	0.034**	0.003
	(0.024)	(0.024)	(0.024)	(0.024)	(0.016)	(0.002)
productivity	-0.002	-0.002	-0.002	-0.002	-0.113***	0.001
	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.002)
pccapital	0.106***	0.102***	0.105***	0.102***	-0.011	0.005***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.012)	(0.002)
rdinput	0.165***	0.153***	0.162***	0.153***	0.056	0.005***
	(0.039)	(0.036)	(0.039)	(0.037)	(0.037)	(0.002)
population	0.102	0.198	0.126	0.201	0.034	0.029
	(0.228)	(0.243)	(0.231)	(0.244)	(0.263)	(0.018)
pcgdp	0.833***	0.794***	0.830***	0.796***	0.476***	0.042***
	(0.268)	(0.255)	(0.263)	(0.254)	(0.178)	(0.016)
pcroad	0.038	0.030	0.035	0.030	0.020	0.005
	(0.050)	(0.049)	(0.050)	(0.049)	(0.057)	(0.004)
firm	1.253***	1.248***	1.255***	1.249***	0.678***	0.055***
	(0.082)	(0.081)	(0.082)	(0.081)	(0.119)	(0.004)
Prefecture-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	219,514	219,514	219,514	219,514	219,514	169,545
R^2	0.698	0.699	0.699	0.699	0.777	0.631
Adjusted R^2	0.624	0.624	0.624	0.624	0.722	0.513
Residual Std. Error	3.729 (df = 176086)	3.728 (df = 176085)	3.729 (df = 176084)	3.728 (df = 176083)	1.636 (df = 176083)	0.287 (df = 128443)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01					

Table 4 Foreign MNEs' spillover channels in export sophistication

	Dependent variable:			
	dompci			
	(1)	(2)	(3)	(4)
MNE	0.001	0.001	0.001	0.0002
	(0.006)	(0.006)	(0.006)	(0.006)
relMNE		0.015		0.006
		(0.011)		(0.010)

flMNE			0.019**	0.018***
			(0.007)	(0.007)
blMNE			0.0002	-0.0005
			(0.005)	(0.005)
nebMNE	-0.001	-0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
productivity	0.002	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
pccapital	-0.002	-0.002	-0.002	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)
rdinput	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
population	0.053**	0.064**	0.066**	0.069**
	(0.026)	(0.031)	(0.029)	(0.033)
pcgdp	0.051*	0.048*	0.049*	0.048*
	(0.030)	(0.029)	(0.029)	(0.029)
pcroad	0.002	0.002	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)
firm	-0.004	-0.004	-0.003	-0.003
	(0.005)	(0.004)	(0.004)	(0.004)
Prefecture-industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	53,828	53,828	53,828	53,828
R^2	0.912	0.912	0.912	0.912
Adjusted R^2	0.879	0.879	0.880	0.880
Residual Std. Error	0.315 (df = 39433)	0.315 (df = 39432)	0.315 (df = 39431)	0.315 (df = 39430)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Regional and industry heterogeneity

The role of MNEs may change according to the contextual features of the region they are based in (e.g., because of quality of government, policies, etc.) as well as due to industry specificities. In this section we explore these heterogeneous effects, as illustrated in Table 5. First, we subsample our datasets into two datasets according to the location of firms. Of the two regions, the Eastern region (for short, ER) typically includes the most developed economic areas of China, the non-Eastern region (for short, NER) includes the Central, the Western and the Northeastern regions, which are relatively less developed. Second, we look at industry heterogeneity by splitting our dataset in two groups: high-knowledge industries (HKI) and low-knowledge industries (LKI).

They are built using the industry categories defined by Patent Intensive Industry Catalog 2016 (Trial) (as shown in Table A3 in Appendix A). In models (1)-(4) in Table 5, we explore the heterogeneous effects of MNE presence on export quantity. The signs of our variables of interest largely confirm the base-line estimates. Interestingly, the effect of MNEs in related industries is larger for lagging regions (NER region) and high-knowledge industries. We interpret this result as follows: developed regions are endowed with stronger capabilities, thus they tend to rely less on MNEs, while lagging regions, which lack relevant knowledge on export activities, benefit more from spillovers provided by MNEs in related sectors. A similar logic applies to high-knowledge industries, as they have higher absorptive capability, they can grasp more than low-knowledge intensive industries, the spillovers of MNE.

In models (5)-(8) in Table 5, we explore the heterogeneous effects of MNE presence on export sophistication. The results seem to suggest that our general findings are mainly driven by developed regions (ER region). We can think of two main reasons for this. First, as shown in Figure C3, MNEs are mainly concentrated in the Eastern region of China. Due to the severe competition among MNEs to occupy local markets, it is easier for domestic firms in the Eastern region to obtain high-quality and less costly inputs than their counterparts in the Central and Western regions. Second, the knowledge required to upgrade products is both specific to the product and production processes and usually more complex than the one needed for export activities. Therefore, domestic firms in lagging regions, which often lack absorptive capacity, are less able to reap the benefits of knowledge spillovers from MNEs. We also notice that the coefficient of *flMNE* is larger in size and more significant for low-knowledge industries (LKI) than for high-knowledge industries (HKI). This finding is not surprising, as global value chains organised by MNEs are pervasive in low-knowledge industries, which benefit from insertion in these value chains. Interestingly, the coefficient of *blMNE* is even negative and significant for high-knowledge industries (HKI). Therefore, industries in HKI that supply MNEs would experience a decrease in export complexity. This finding is also not surprising, indeed downgrading strategies have been found in several cases of supplier-dominated value chains, where local suppliers struggle to upgrade their export basket under the competition pressure of downstream MNEs (Rabellotti, 2004).

Table 5 The regional and industrial heterogeneities

	Dependent variable:							
	domexp (ln)				*dompci*			
	ER	NER	HKI	LKI	ER	NER	HKI	LKI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MNE	-0.436***	-0.211***	-0.358***	-0.331***	0.003	-0.012	-0.005	0.003
	(0.055)	(0.057)	(0.057)	(0.051)	(0.008)	(0.009)	(0.014)	(0.006)
relMNE	0.400***	0.848***	0.625***	0.383***	0.007	0.034	0.024	-0.003

	(0.105)	(0.199)	(0.155)	(0.110)	(0.010)	(0.050)	(0.017)	(0.012)
flMNE	0.048	0.073	-0.076	0.088	0.020***	0.005	0.010	0.022**
	(0.083)	(0.070)	(0.091)	(0.084)	(0.007)	(0.013)	(0.006)	(0.010)
blMNE	-0.040	0.020	-0.118	0.029	0.0003	-0.004	-0.014*	0.004
	(0.066)	(0.071)	(0.128)	(0.058)	(0.005)	(0.011)	(0.008)	(0.006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107,512	112,002	70,572	148,942	37,446	16,382	18,094	35,734
R^2	0.691	0.661	0.674	0.710	0.899	0.938	0.796	0.911
Adjusted R^2	0.623	0.569	0.594	0.639	0.867	0.909	0.718	0.879
Residual Std. Error	4.214 (df = 87934)	3.144 (df = 88130)	3.848 (df = 56600)	3.667 (df = 119464)	0.327 (df = 28240)	0.281 (df = 11171)	0.325 (df = 13093)	0.309 (df = 26318)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01							

Robustness checks

We carry out additional checks to test for the robustness of our results (see Appendix D). In Table D1, we further include prefecture-year and industry-year fixed effects to alleviate possible omitted variable bias. In Table D2, we use the share of MNE employment rather than share of MNEs over total firms to capture the presence of MNEs in our key explanatory variables, since firms may be quite heterogenous in terms of size. In Table D3, we further control for the share of MNEs in unrelated industries to test whether our findings are influenced by MNEs in unrelated industries, for instance due to agglomeration effects. In Tables D4 and D5, we split MNEs into two groups by country of origin to explore the heterogeneity of MNEs. In Table D6, we exclude domestic firms which were established after 2000 to test whether our findings hold for incumbents and is not driven by spatial sorting of new firms. In Table D7, we aggregate the share of MNEs in forward and backward industries at 3-digit level. All the above different settings lead to some variations in the relative magnitudes of the estimates for our variables of interest, but there is no systematic deviation from the general findings outlined above.

Conclusion and Discussion

China has been, and continues to be, one of the world's top recipients of FDI (WIR, 2023). Foreign MNEs have arguably played a crucial role in the modernisation of the Chinese economy, favouring the upgrading of the domestic manufacturing and service sectors. In this paper, we focus on how knowledge spillovers from MNEs may have facilitated the expansion and upgrading of Chinese domestic exports. More specifically, we investigate three different channels (i.e., horizontal linkages, vertical linkages, relatedness linkages) through which MNE spillovers affect the export of domestic firms in Chinese regions. In short, we find that horizontal and relatedness linkages matter, respectively in a negative and positive way, for export quantity, in terms of increasing the number of exporters and penetrating new markets. Differently, vertical (i.e. forward) linkages matter for export quality, in terms of higher sophistication of exported goods. We interpret our findings building on previous studies (Blyde et al., 2004; Kneller & Pisu, 2007) that identify a variety of mechanisms through which these channels transmit different types of knowledge spillovers to domestic firms. For example, we find that 'relatedness' linkages play a more important role in the diffusion of marketing-related knowledge, consisting of either knowledge about distribution networks in export destinations and the international business environment and practices. Our expectations and findings are consistent with previous evidence showing the importance of information spillovers for international trade (Mion et al., 2016; Bisztray et al., 2018; Ramos & Moral-Benito, 2018) and the relatedness channel in the diffusion of marketing as opposed to product or production practices (Jun et al., 2017). We also find that forward linkages are responsible for production-related spillovers, such as information on material inputs or production processes. As domestic firms are involved in some form of vertical chains with MNEs, they are in a better position to access some proprietary knowledge embodied in MNEs' products (Driffield et al., 2002). For these reasons, we argue that forward linkages play a crucial role in channeling production-specific knowledge. Our findings are in line with other studies, such as Javorcik et al. (2018), who conducted a similar investigation on Turkish firms.

With our work, we make three main contributions.

First, we develop a comprehensive framework in which we connect different strands of literatures to better understand and conceptualize export spillovers from foreign firms. Our framework systematically connects five different but related dimensions (mechanisms, spillover channels, activation, knowledge type and impact) to shed some light on the interactions between these dimensions. Second, we add to the literature on MNE spillovers by showing that relatedness is an important channel for knowledge spillovers. This is shown to be true at least in the specific case of export-facilitating MNE spillovers. Third, as discussed above, we show that among the cross-industry channels of MNE externalities, relatedness and vertical linkages are likely to transmit different types of export-relevant knowledge to domestic firms (Blyde et al., 2004; Kneller & Pisu, 2007). This evidence adds to the broader theoretical debate on relatedness. Despite the great success in explaining regional diversification in empirical studies (Neffke et al., 2011; Muneepeeraku et al., 2013; Rigby, 2015; Boschma et al., 2015; Shutters et al., 2016; Zhu et al., 2017; Boschma, 2017; Balland et al., 2019; Farinha et al., 2019; Gao et al., 2021), “relatedness” has been criticised for being an 'agnostic' measure (Bahar et al., 2019) that does not provide an understanding of what kind of knowledge or skills are diffused through ‘relatedness’ ties. Our research contributes to this debate by suggesting that relatedness linkages and forward-backward linkages play different roles in diffusing marketing-related and product-related knowledge in the context of export activities.

A number of policy implications could be drawn from our work by looking at the different mechanisms and channels through which MNEs affect domestic exports. For example, we have shown that several mechanisms (e.g. imitation/demonstration, labour mobility) generate positive spillovers to domestic companies in either related sectors (i.e. relatedness spillover channel) or inserted in MNEs value chains (i.e. forward spillover channel). To reinforce these positive effects, policies may then provide incentives to attract FDIs with the highest potential to generate such spillovers. This is what China has been doing since the beginning of the 'open door' policy, using various forms of selective industrial policies to attract FDIs or imposing various performance requirements to maximise access to foreign knowledge (Zheng, 2019). Although compulsory performance requirements were formally abolished with China's accession to the WTO, many are still in place, albeit listed as 'voluntary', and appear to play a role in generating positive knowledge spillovers (Long, 2005). For example, these requirements may facilitate interactions between domestic and foreign firms through worker training or technical assistance. More recently, China has developed other incentive schemes either to attract foreign firms in fast-growing sectors (e.g. clean technology) or to retain firms by improving the overall business climate (enforcement of property rights, greater transparency, access to preferential treatment)[3]. Taken together, these measures can play a role in enhancing the impact of knowledge spillovers that domestic firms can gain from MNEs.

Another way in which our results provide some useful policy insights concerns the geographical dimension of the impact of MNEs. For example, we show that lagging regions benefit more from absorbing knowledge related to marketing practices than more developed regions in China, while this is not the case for product sophistication. This finding seems to suggest that lagging regions fail to absorb external knowledge due to a lack of appropriate human capital and knowledge-specific assets. This leaves room for policy interventions that promote the development of indigenous capabilities needed to benefit from MNE spillovers. Indeed, this has been a recent feature of China's industrial policy, which is increasingly concerned with developing peripheral regions relative to the already developed coastal regions, for example through tax breaks or the creation of special zones.

This paper is not without limitations. First, we are not able to directly observe the specific

[3] Information retrieved from the State Council Information Office (PRC) http://english.scio.gov.cn/topnews/2021-02/23/content_77239886.htm and https://english.www.gov.cn/policies/policywatch/202308/14/content_WS64d9680bc6d0868f4e8de85f.html

mechanisms linking MNEs in related industries and export performance. While our reasoning is backed by sound theoretical arguments, future research should aim further specifying the mechanisms behind our findings (e.g., through interviews to exporting domestic firms or using linked employer-employee data). Second, our analysis may suffer from potential endogeneity problems, since MNEs do not choose their locations randomly. Although we have included a comprehensive set of control variables and fixed effects and all independent variables are one year lagged in the model specification, the estimates we presented should not be interpreted in a causal sense. Finally, future studies could further incorporate labour mobility, patent citations and other possible venues for knowledge spillovers in order to explore their possibly different roles in the process of knowledge diffusion from MNEs to domestic firms and industries.

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Appendix A

Table A1 Top and last 10 most complex industries (average complexity of products from domestic firms)

Order	Industry code (GB/T 4754－2002)	Industry name	Product complexity index
1	3152	Special ceramic products manufacturing	2.572
2	3551	Bearing manufacturing	2.352
3	3662	Manufacturing of special equipment for the electronics industry	2.352
4	4071	Household film and television equipment manufacturing	2.352
5	3646	Manufacturing of special equipment for the production of glass, ceramics and enamel products	2.339
6	4126	Teaching equipment manufacturing	2.276
7	2619	Manufacturing of special pharmaceutical materials for environmental pollution treatment	2.263
8	2624	Compound fertilizer manufacturing	2.263
9	2651	Primary form of plastic and synthetic resin manufacturing	2.263
10	2652	Synthetic rubber manufacturing	2.263
414	3090	Other plastic products manufacturing	-2.148
415	2130	Metal furniture manufacturing	-2.148
416	2040	Manufacturing of bamboo, rattan, palm and grass products	-2.148
417	2021	Plywood manufacturing	-2.148
418	1769	Manufacturing of other knitwear and knitwear	-2.148
419	1310	Grain milling	-2.148
420	1763	Silk knitwear and knitwear manufacturing	-2.162
421	1761	Manufacture of cotton and chemical fiber knitwear and woven products	-2.162
422	3615	Metallurgical equipment manufacturing	-2.182
423	1535	Solid beverage manufacturing	-2.293

Table A2 The correlation table of main variables

Variables	Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
domexp (ln)	1	1.000															
domnum	2	0.325	1.000														
dommar	3	0.048	0.104	1.000													
dompci	4	-0.038	-0.112	0.070	1.000												
MNE	5	0.054	0.055	0.124	-0.069	1.000											
relMNE	6	0.093	0.081	0.176	0.050	0.633	1.000										
flMNE	7	0.114	0.057	0.129	0.070	0.512	0.726	1.000									
blMNE	8	0.071	0.073	0.118	-0.046	0.474	0.665	0.610	1.000								
nebMNE	9	0.067	0.099	0.073	-0.104	0.433	0.489	0.419	0.367	1.000							
productivity	10	0.044	-0.014	0.037	0.038	0.010	0.036	0.021	0.031	-0.012	1.000						
pccapital	11	0.026	-0.022	0.004	0.049	0.008	0.028	0.032	0.018	-0.026	0.384	1.000					
rdinput	12	0.104	0.042	0.102	0.081	0.315	0.577	0.415	0.356	0.216	0.045	0.069	1.000				
population	13	0.015	0.030	0.093	0.051	-0.013	0.085	0.048	0.025	-0.113	0.010	0.029	0.260	1.000			
pcgdp	14	0.116	0.076	0.135	0.082	0.432	0.623	0.453	0.421	0.377	0.050	0.034	0.589	-0.087	1.000		
pcroad	15	0.089	0.061	0.126	0.075	0.328	0.457	0.349	0.323	0.300	0.052	0.009	0.369	-0.110	0.779	1.000	
firm	16	0.249	0.730	0.101	-0.082	0.145	0.232	0.168	0.191	0.179	0.002	-0.018	0.159	0.092	0.151	0.103	1.000

Table A3 Patent-intensive industries in China defined by *Patent Intensive Industry Catalog 2016 (Trial)*

Industry category	**Industry subcategory code**	**Industry subcategory**
Information Basic Industry	391	Computer manufacturing
	392	Communication equipment manufacturing
	393	Radio and television equipment manufacturing
	394	Radar and ancillary equipment manufacturing
	396	Electronic device manufacturing
Software and information technology service industry	651	Software development
	652	Information system integration service
	653	Information technology consulting service
	654	Data processing and storage services
	655	IC design
	659	Other information technology service industry
Modern Transportation Equipment Industry	361	Automobile manufacturing
	366	Auto parts and accessories manufacturing
	371	Railway transportation equipment manufacturing
	374	Aviation, spacecraft and equipment manufacturing
Intelligent manufacturing equipment industry	342	Metal processing machinery manufacturing
	343	Material handling equipment manufacturing
	351	Manufacturing of special equipment for mining, metallurgy, and construction
	354	Manufacturing of special equipment for printing, pharmacy, daily chemical and daily necessities production
	355	Manufacturing of special equipment for textile, clothing and leather processing
	356	Manufacturing of special equipment for electronics and electrical machinery
	357	Manufacturing of special machinery for agriculture, forestry, animal husbandry and fishery
Biomedical Industry	271	Chemical raw material manufacturing
	272	Chemical preparation manufacturing
	273	Chinese herbal medicine processing
	274	Chinese patent medicine production
	276	Biopharmaceutical manufacturing
	358	Medical equipment and machinery manufacturing
	404	Optical instrument and glasses manufacturing
New functional material industries	261	Basic chemical raw material manufacturing
	263	Pesticide manufacturing
	264	Manufacturing of coatings, inks, pigments and similar products
	265	Synthetic material manufacturing
	266	Special chemical product manufacturing
	268	Daily chemical product manufacturing
High-efficiency, energy-saving	341	Boiler and prime mover equipment manufacturing
	344	Pumps, valves, compressors and similar machinery manufacturing

and environmental protection industry	346	Manufacturing of ovens, fans, weighing instruments, packaging and other equipment
	352	Manufacturing of special equipment for chemical, wood, and non-metal processing
	359	Environmental protection, social public service and other special equipment manufacturing
	382	Manufacturing of power transmission and distribution and control equipment
	384	Battery manufacturing
	387	Lighting equipment manufacturing
	401	General instrumentation manufacturing
	402	Special instrument and meter manufacturing
Resource recycling industry	336	Metal surface treatment and thermal processing
	462	Sewage treatment and recycling
	469	Other water treatment, utilization and distribution

Appendix B

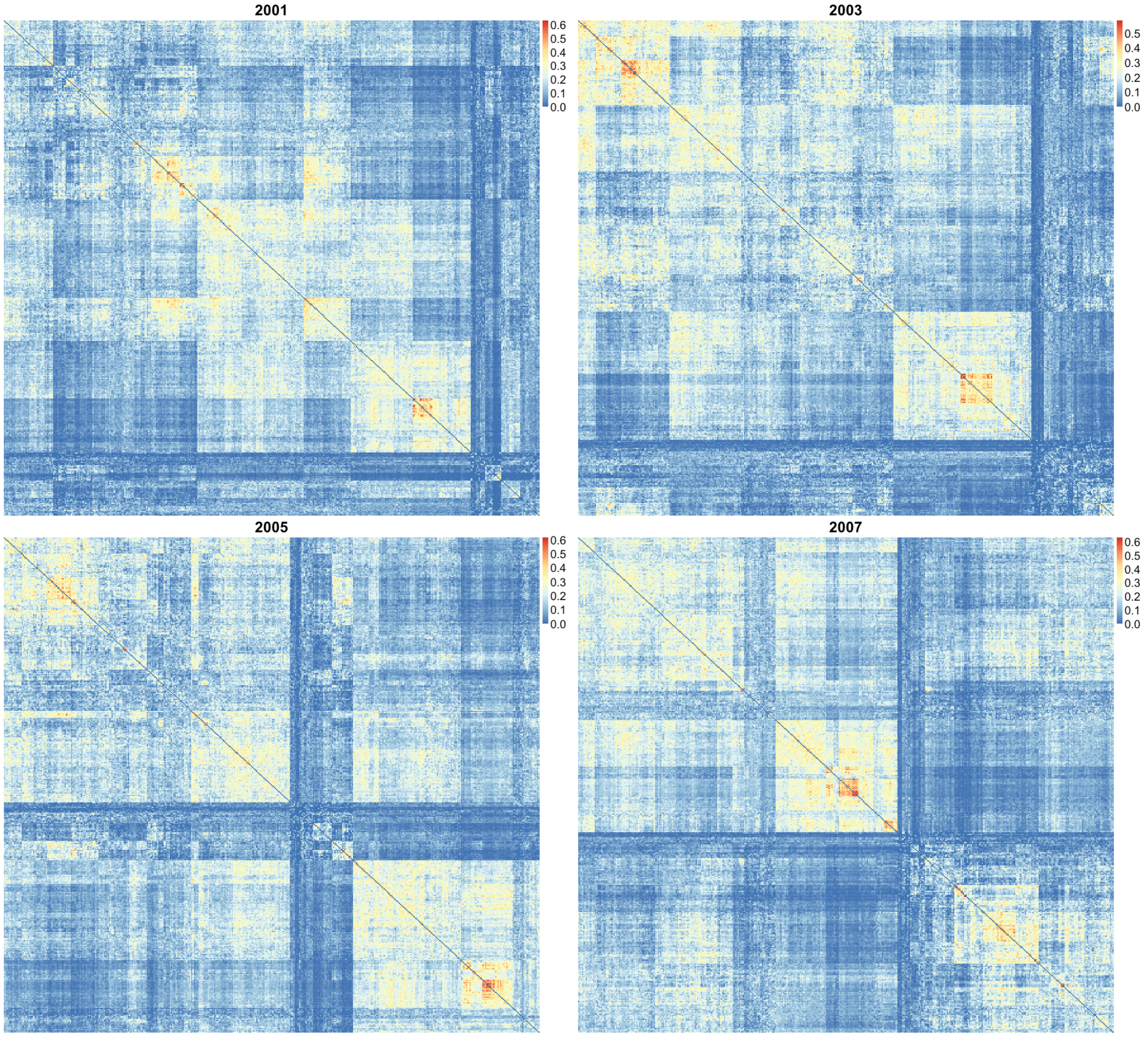

Figure A1 The hierarchically clustered relatedness heatmap of Chinese industries in 2001/2003/2005/2007

Appendix C

In this section, we first present the general trend of export quantity and complexity by domestic firms across Chinese prefectures. Figure C1 reports the spatial distribution of total export quantity of domestic firms in all industries in Chinese prefectures in 2001/2003/2005/2007. At national level, the level of export quantity of Chinese prefectures is increasing year by year in general, and the spatial pattern of export quantity shows a gradient descent trend from the coastal area to inland area, which reflects somehow the different stages of economic development of Chinese regions. Prefectures with highest export quantity are mainly located in the Yangtze River Delta area, the Beijing-Tianjin-Hebei area, the Pearl River Delta area, and capital cities of some central and western provinces. In Figure C2, we plot the sum of the complexity of all industrial exports by domestic firms for Chinese prefectures. Negative (positive) values of the complexity measure indicate lower (higher) sophistication exports, so the higher the total complexity score is, the higher is the sophistication of goods exported by a prefecture. The spatial distribution also shows a similar pattern with export quantity. In Figure C3, we present the spatial distribution of the share of MNEs on the total number of firms in Chinese prefectures in 2001/2003/2005/2007. Also, in this case it emerges a clear pattern with coastal regions having a higher share of MNEs. It is worth mentioning that the spatial pattern of MNEs is not perfectly matching the spatial pattern of export quantity and sophistication, with the former more concentrated in Pearl River Delta area (Southern part). This may be due to the large influx of MNEs from Hongkong, Macau, and Taiwan in the early 21st century in this area.

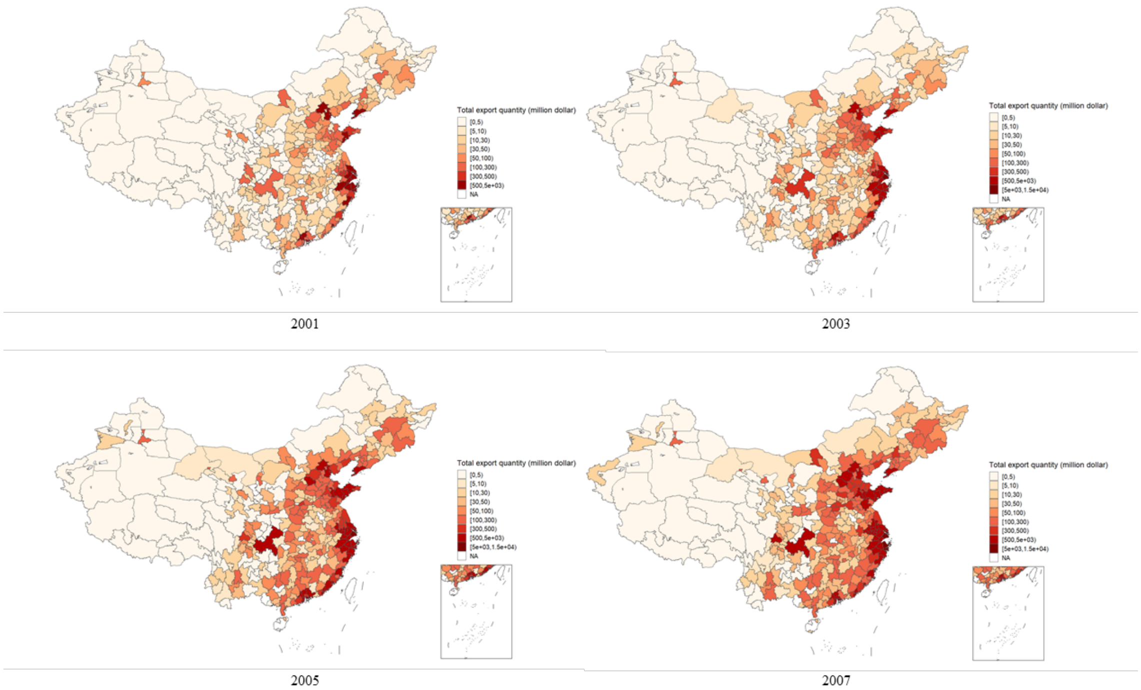

Figure C1 The spatial distribution of export quantity in Chinese prefectures in 2001/2003/2005/2007

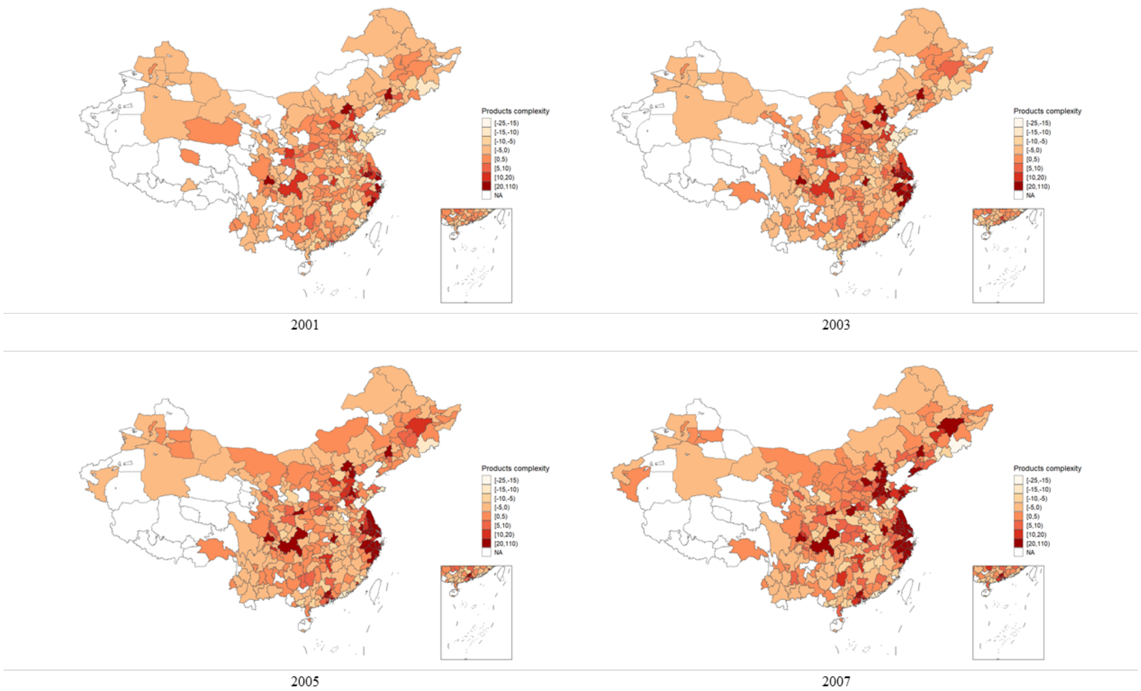

Figure C2 The spatial distribution of export complexity in Chinese prefectures in 2001/2003/2005/2007

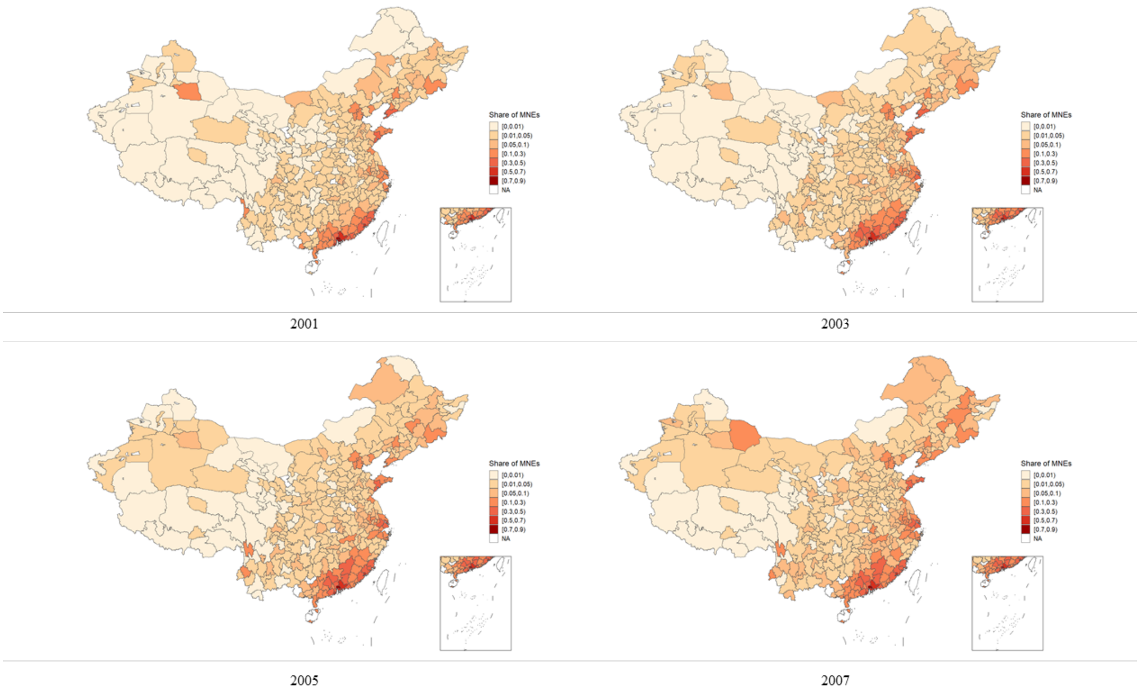

Figure C3 The spatial distribution of share of MNEs in Chinese prefectures in 2001/2003/2005/2007

In Figure C4, we present the scatterplots between export quantity and share of MNEs in the same industry, related, forward, and backward industries in the starting and ending year of the sample period respectively. We observe that export quantity appears to be positively and significantly associated with all types of MNE presence, however, the correlation coefficients with inter-industry MNE presence are much larger than the one with MNE presence in the same industry. Similarly, the correlation between export complexity and share of MNEs is explored in Figure C5. The results indicate that export complexity is only positively and significantly correlated with share of MNEs in the forward industries both in the starting year and ending year. Moreover, export complexity is even negatively associated with share of MNEs in the same industry and backward industries. However, due to the existence of prefecture, industry, and year heterogeneities, correlation analysis may be biased. In the next section, we further conduct econometric analysis to investigate the relationship between the dependent variables and variables of interest.

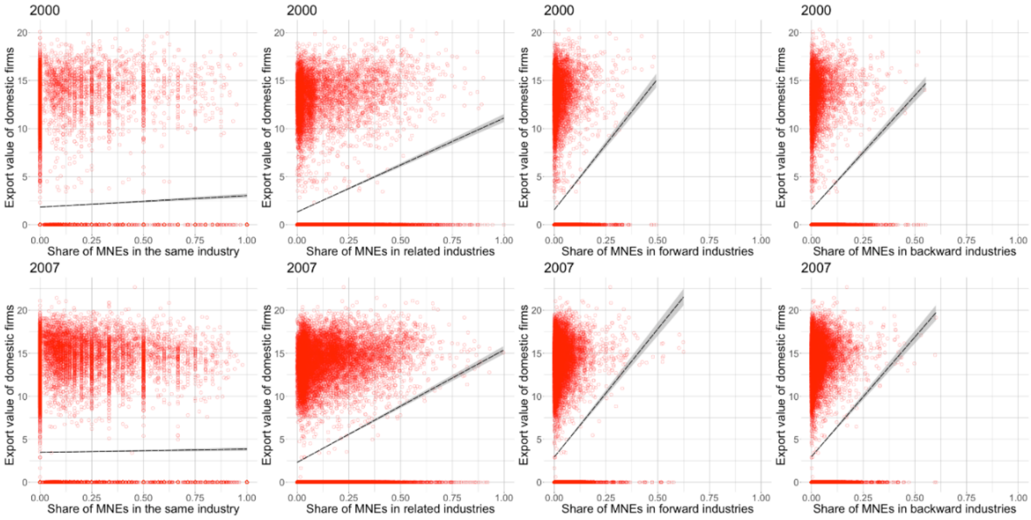

Figure C4 The scatterplot of export quantity and share of MNEs in 2000/2007

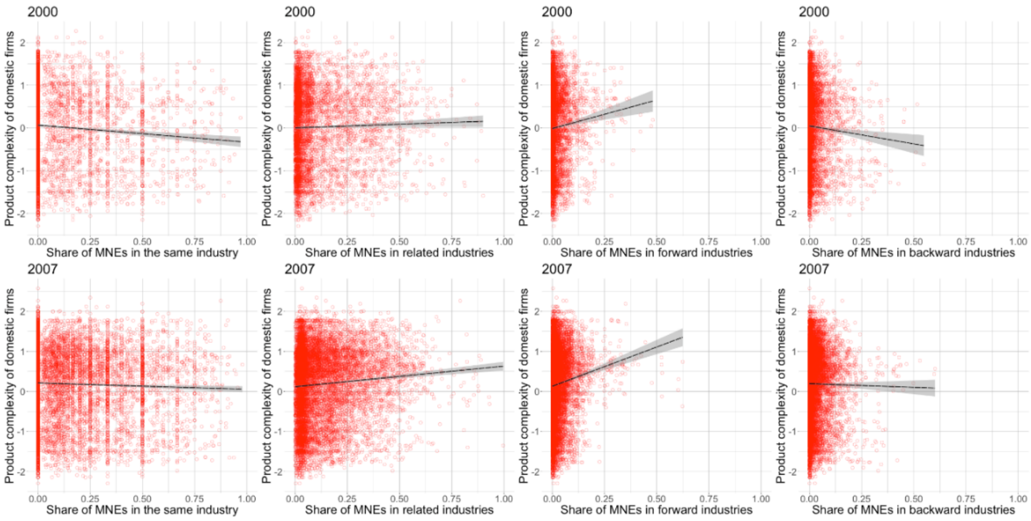

Figure C5 The scatterplot of export complexity and share of MNEs in 2000/2007

Appendix D

We check the robustness of our results in several different settings. In Table D1, we further restrict our model by including prefecture-year and industry-year fixed effects to control all the prefecture and industry level time varying factors which could affect the industry entry. Due to the inclusion of these fixed effects, the effects of all prefecture-level and industry-level variables (such as regional and industrial policy shock) are absorbed by them, so the prefecture-level and industry-level variables are not included in Table D1. Except a few minor changes, the results are quite in line with our previous findings, thus further consolidating our expectations.

Then, in Table D2, we use the share of MNE employment rather than the share of number of MNEs as our key explanatory variables (*MNE*, *relMNE* and *flMNE, blMNE* are all replaced respectively). The logic behind this lies in that firms may be quite heterogeneous in size, and making use of the number of employments could address the size effect of different companies. The results are quite in line with all our previous findings.

In Table D3, we further control the average share of MNEs in the unrelated industries of the focal industry (*unrelMNE*), which turns out to be negative and significant in several cases. This may be due to the significant cognitive gap between unrelated industries, thence, domestic firms could not benefit from MNEs in their unrelated industries. Moreover, the presence of MNEs in unrelated industries could attract high-quality human capital and resources which otherwise could be employed by domestic firms. In this situation, MNEs in unrelated industries could do harm to domestic firms. All our variables of interest are still positive and significant. This further consolidates previous findings.

In Table D4 and Table D5, we split the MNEs into two groups by country of origin, that is, MNEs from Hong Kong, Macau, and Taiwan, and the rest ones from other foreign countries, and calculate the variables of interest respectively. The results in Table D4 show that relatedness linkages with MNEs from Hong Kong, Macau, and Taiwan still have a positive and significant impact for the export quantity growth and new market entry of domestic firms. However, forward linkages with MNEs are no longer significant for the complexity of exporting products. The results in Table D5 further verify the preliminary findings of this paper. Compared with Table D4, the results in Table D5 show that our results are mainly driven by foreign MNEs.

Moreover, domestic firms may tend to agglomerate in regions with more MNEs to capture exporting knowledge spillovers, and this will enhance the regional exporting activities by attracting more domestic firms. In order to test whether the relation between MNEs and exports is driven by spatial sorting of new firms, in Table D6, we only keep domestic firms which where already located in the region before 2000. The results show that our main findings still hold for incumbents.

Finally, rather than equally splitting the strength of forward and backward linkages among 3-digit industries to corresponding 4-digit subgroups, we aggregate the share of MNEs in forward and backward industries at 3-digit level directly. The results are presented in Table D7. Compared with the splitting approach, the aggregation approach may reduce the estimation precision due to coarsened information in variables *flMNE* and *blMNE*. However, the results are still consistent with our main findings.

In sum, although there are a few minor differences in the results of robustness checks, we do not find systematical deviations from our main findings. Thus, our results are robust under a series of alternative checks.

Table D1 Robustness check with prefecture-year and industry-year fixed effects

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.353***	-0.178***	-0.011***	0.0003
	(0.040)	(0.032)	(0.003)	(0.005)
relMNE	0.855***	0.438***	0.038***	-0.016
	(0.135)	(0.130)	(0.010)	(0.022)
flMNE	0.019	0.019	0.0002	0.022***
	(0.071)	(0.055)	(0.005)	(0.007)
blMNE	0.038	0.040	0.003	0.003
	(0.056)	(0.064)	(0.004)	(0.005)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	238,222	180,490	55,708
R^2	0.712	0.799	0.647	0.923
Adjusted R^2	0.632	0.743	0.521	0.880
Residual Std. Error	3.628 (df = 186270)	1.515 (df = 186270)	0.280 (df = 132963)	0.314 (df = 35854)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D2 Robustness check with share of MNE employment

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.329***	-0.124***	-0.008***	-0.001
	(0.044)	(0.022)	(0.003)	(0.005)

relMNE	0.900***	0.538***	0.039***	-0.015
	(0.133)	(0.155)	(0.010)	(0.018)
flMNE	0.039	0.071	0.002	0.022***
	(0.074)	(0.057)	(0.005)	(0.007)
blMNE	-0.013	0.031	0.0003	0.004
	(0.052)	(0.064)	(0.004)	(0.004)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	238,222	180,490	55,708
R^2	0.712	0.799	0.647	0.923
Adjusted R^2	0.632	0.743	0.521	0.880
Residual Std. Error	3.627 (df = 186270)	1.515 (df = 186270)	0.280 (df = 132963)	0.314 (df = 35854)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D3 Robustness check with unrelated MNEs

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.353***	-0.178***	-0.011***	0.0003
	(0.040)	(0.032)	(0.003)	(0.005)
relMNE	0.826***	0.414***	0.037***	-0.015
	(0.138)	(0.129)	(0.011)	(0.022)
unrelMNE	-0.684*	-0.563**	-0.019	0.025
	(0.401)	(0.219)	(0.035)	(0.031)
flMNE	0.020	0.019	0.0003	0.022***
	(0.071)	(0.055)	(0.005)	(0.007)
blMNE	0.037	0.040	0.003	0.003
	(0.056)	(0.063)	(0.004)	(0.005)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes

Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	238,222	180,490	55,708
R^2	0.712	0.799	0.647	0.923
Adjusted R^2	0.632	0.743	0.521	0.880
Residual Std. Error	3.627 (df = 186269)	1.515 (df = 186269)	0.280 (df = 132962)	0.314 (df = 35853)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D4 Robustness check with only HK-Macau-Taiwan MNEs

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.219***	-0.170***	-0.037***	-0.005
	(0.034)	(0.025)	(0.004)	(0.007)
relMNE	0.441***	0.137	0.037**	0.006
	(0.118)	(0.118)	(0.015)	(0.021)
flMNE	0.028	0.016	-0.002	0.003
	(0.053)	(0.050)	(0.004)	(0.006)
blMNE	-0.017	0.070*	0.003	-0.003
	(0.044)	(0.040)	(0.004)	(0.003)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	208,697	151,542	47,285
R^2	0.712	0.801	0.666	0.928
Adjusted R^2	0.631	0.740	0.527	0.883
Residual Std. Error	3.629 (df = 186270)	1.401 (df = 159166)	0.264 (df = 107233)	0.311 (df = 29014)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D5 Robustness check with only foreign MNEs

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.193***	-0.157***	-0.042***	0.002
	(0.031)	(0.020)	(0.003)	(0.005)
relMNE	0.755***	0.314**	0.052***	0.004
	(0.152)	(0.129)	(0.014)	(0.015)
flMNE	-0.003	-0.009	0.002	0.015**
	(0.038)	(0.024)	(0.003)	(0.006)
blMNE	0.042	0.003	0.003	-0.011***
	(0.036)	(0.031)	(0.003)	(0.004)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	208,697	151,542	47,285
R^2	0.712	0.801	0.667	0.928
Adjusted R^2	0.631	0.740	0.529	0.883
Residual Std. Error	3.629 (df = 186270)	1.400 (df = 159166)	0.269 (df = 107233)	0.311 (df = 29014)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D6 Robustness check without domestic firms established after 2000

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.487***	-0.169***	-0.070***	0.001
	(0.043)	(0.018)	(0.005)	(0.006)
relMNE	0.814***	0.216***	0.060***	0.012
	(0.158)	(0.063)	(0.018)	(0.013)
flMNE	0.022	-0.001	0.003	0.015***
	(0.047)	(0.012)	(0.004)	(0.005)
blMNE	-0.041	0.054	0.002	-0.016*
	(0.045)	(0.032)	(0.003)	(0.008)
Control variables	Yes	Yes	Yes	Yes

Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	202,586	173,167	118,286	37,864
R^2	0.705	0.857	0.660	0.935
Adjusted R^2	0.620	0.811	0.512	0.891
Residual Std. Error	3.562 (df = 157040)	0.841 (df = 130777)	0.274 (df = 82413)	0.301 (df = 22516)
Note:	All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01			

Table D7 Robustness check with 3-digit industry

	Dependent variable:			
	domexp (ln)	*domnum*	*dommar*	*dompci*
	(1)	(2)	(3)	(4)
MNE	-0.504***	-0.176***	-0.027***	-0.003
	(0.046)	(0.035)	(0.004)	(0.007)
relMNE	1.120***	0.407**	0.077***	0.016
	(0.179)	(0.157)	(0.016)	(0.019)
flMNE	0.002	0.021	0.003	0.011*
	(0.033)	(0.039)	(0.003)	(0.006)
blMNE	0.005	0.056	0.001	-0.009*
	(0.036)	(0.039)	(0.004)	(0.005)
Control variables	Yes	Yes	Yes	Yes
Prefecture-industry FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Observations	238,222	238,222	180,490	55,708
R^2	0.713	0.798	0.652	0.923
Adjusted R^2	0.634	0.742	0.529	0.880
Residual Std. Error	3.524 (df = 186270)	1.437 (df = 186270)	0.259 (df = 132963)	0.314 (df = 35854)

Note: All standard errors are robust standard errors clustered at prefecture and 3-digit industry level; *p<0.1; **p<0.05; ***p<0.01