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Abstract

In this paper, we explore how spillovers from multinational enterprises (MNEs) spread and impact domestic firms through different channels and at various spatial scales. Taking a firm-level approach, we test whether industrial relatedness mediates spillover effects from MNEs over and above horizontal and vertical linkages traditionally identified by the literature. Thanks to fine-grained geographical information, we further investigate the spatial reach of the spillovers and how they are associated with domestic firms' characteristics such as absorptive capacity and technological sophistication. Our hypotheses are tested on a panel data set of Indonesian manufacturing firms census between 2002 to 2009. We find that domestic firms have higher total factor productivity when being exposed to a higher share of output from multinational firms in related industries, on top of the widely acknowledged horizontal and vertical MNE spillovers. We also show that MNE spillovers are sensitive to distance, with relatedness-mediated ones being detected between 30 and 60 km from the municipality of the MNE. Regarding heterogeneity, large firms benefit from productivity-enhancing relatedness spillovers at a wider spatial

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distance (up to 90km), and firms in less-advanced industries benefit from relatedness mediated effects as much as those in more advanced industries.

JEL codes: D24, F23, O33, R10

Keywords: Multinational enterprises, spillovers, industrial relatedness, spatial effects.

1 Introduction

The processes and dynamics through which knowledge diffuses across space are not random and are mostly driven by a mix of cognitive, social and spatial proximity (Boschma, 2005; Jaffe et al., 1993; Breschi and Lissoni, 2009; van der Wouden and Rigby, 2019). Building on this understanding, various contributions have highlighted how similarity (or relatedness) across products and industries plays a crucial role in shaping the evolutionary trajectory of an economy (Hidalgo et al., 2007; Boschma and Capone, 2015; Cortinovis et al., 2017). Increased relatedness among two industries implies relatively low costs for a firm to diversify from one into the other because the knowledge, capital and technological assets to operate in the new industry are similar to those already possessed by the firm. The general and consistent support for these ideas in a number of different settings has led scholars to propose "relatedness" as an empirical scientific principle (Hidalgo et al., 2018).

Over recent decades, there has been strong interest in examining the impact of the presence of multinational enterprises (MNEs) and their foreign direct investment (FDI) on the performance of domestic firms. In particular, the existence and role of spillovers generated by MNEs have received significant attention. Most of the contributions in the field, however, maintain a close focus on intra-industry or input-output linkages as channels for such externalities (Gorg and Greenaway, 2004; Javorcik, 2004; Meyer and Sinani, 2009; Rojec and Knell, 2018). Whereas the idea of relatedness as an important channel for knowledge diffusion has been recently applied to the case of foreign firms (Lo Turco and Maggioni, 2019; Cortinovis et al., 2020; Boschma, 2017; Howell, 2020), whether and how domestic firms benefit from MNEs in related industries is an important and policy-relevant question that has received little attention so far.

In addition to the lack of attention for cross-industry spillovers of MNEs to domestic firms outside the value chain, the spatial reach of such effects has also been under-investigated. Although it is generally held that the closer in space a firm is to the source of spillovers, the higher their impact (Resmini, 2019; Liang, 2017; Bode et al., 2012), most papers in this field constrain spillovers within administrative borders of regions rather than analysing them in a spatially continuous manner (Halpern and Muraközy, 2007). Considering, on the one hand, the granular nature of location advantages of MNEs (Dunning, 1998; McCann, 2008; Beugelsdijk and Mudambi, 2013) and, on the other hand, the widespread use of FDI attraction agencies for fostering development (Crescenzi et al., 2019; Harding and Javorcik, 2011), an improved understanding of the spatial dimension of MNE spillovers can offer important insights to both academics and policy-makers.

In this paper, we combine the relatedness approach, popular in the economic geography literature, with the traditional perspective on input-output linkages to investigate the relevance and spatial scales of different channels for MNE spillovers. Using the Indonesian manufacturing firms census from 2002 to 2009, we begin by examining whether the productivity of domestic firms is associated with the presence of MNEs in the same industry and across industrial sectors through backward, forward and relatedness linkages. We analyse each of these channels individually and at different spatial scales. Because the findings of the first part of the analysis indicate close and medium distance spillovers as the most relevant, in the second part of our empirical work, we incorporate all spillover channels in a unified framework. In this way, we can evaluate the optimal spatial reach of different channels of MNE spillovers and their possible spatial decay. Besides, we focus on important characteristics of domestic firms through which the spillovers mediate: absorptive capacity and technological sophistication. We can, therefore, check whether the ability of domestic firms to benefit from MNE spillovers at different spatial distance is heterogeneous and associated with specific characteristics of the recipient firm.

Our main findings are the following. Domestic firms have higher total factor productivity when being exposed to a higher share of output from multinational firms in related industries, on top of the widely acknowledged horizontal and vertical MNE spillovers. The relatedness-mediated spillovers are sensitive to distance, which can only be detected between 30 and 60 km, which reinforces the mechanism of face-to-face communication in learning from related industries. Direct business interaction is much more likely to take place among neighbouring firms. Regarding heterogeneity, large firms could benefit from productivity-enhancing relatedness spillovers at a wider spatial reach (up to 90km), and firms in less-advanced industries benefit from relatedness mediated effects as much as those in more-advanced industries.

These findings have important implications for both academics, policy-makers and stakeholders. At the firm level, investment in developing business connections with related MNEs might be well rewarded and enhance the positive spillovers. Learning from related industries enables firms to better utilise production technology or input material and thereby improve product quality. At the regional level, the maximum distance that we can detect is 60 km, implying that the benefit from related industries at best can spillover to neighbouring cities, and not any farther. This distance factor is particularly important if local urban planners can realise the potential benefit to bond neighbouring cities together towards a coherent region specialised in a broad set of industries. At the national level, policy-makers should keep in mind that the overall industrial variety presents localised patterns and determine what instruments are best to promote the optimal spatial distribution of MNE spillovers.

Our paper enriches the understanding of MNE spillovers in various ways. First, we contribute to a growing literature (Lo Turco and Maggioni, 2019; Cortinovis et al., 2020) that goes beyond the traditional treatment of inter-industry MNE externalities. We complement MNE spillovers via input-output linkages with industrial relatedness in order to shed light on possible alternative channels for MNE externalities through more encompassing agglomeration dynamics. Second, our study fills in the gap in international business research by studying fine-grained spatial effects of MNE spillovers in a sub-national context (Beugelsdijk and Mudambi, 2013; Mudambi et al., 2018). This work provides some answers on what is the optimal geographical reach of MNE spillovers and some possible indications for local policy-makers. Third, our heterogeneity analysis implies that domestic firms in low-tech industries, which are arguably least likely to benefit from MNEs, can exploit the benefits obtained from the opportunities of learning from related industries as well as in more advanced sectors. Besides, the ability to absorb knowledge (proxied by firm size) importantly affects the spatial extent to which domestic firms can benefit from MNE presence. Finally, we contribute to the understanding of how MNEs affect domestic firms in developing economies, for which the diffusion and acquisition of foreign knowledge diffusion is crucial, and only mixed evidence on MNE spillovers has been provided (Lu et al., 2017).

The paper is structured as follows. Section 2 gives an overview of the related literature. Section 3 provides background information regarding the Indonesian context. Section 4 offers a data description and the methodology. Section 5 presents our results. Section 6 gives some concluding remarks.

2 Literature Review

Over recent decades, a number of contributions both in economics and management have studied the relation between multinational enterprises and the performance of domestic firms (Blomström and Kokko, 1998; Meyer and Sinani, 2009; Rojec and Knell, 2018). Whereas the presence of MNEs is likely to impact on the host economy in a number of ways (Barba Navaretti and Venables, 2006; Resmini, 2019), most of the extant empirical literature has focused on spillovers from multinationals.

Typically, these effects are categorised into two groups: horizontal and vertical spillovers. Horizontal spillovers are thought to derive from the presence of foreign multinationals within the same industry. Conceptually, the presence of a multinational in the same industry may be beneficial to domestic firms due to opportunities for knowledge transfer and the adoption of new technologies. At the same time, competition effects to which domestic firms would be subject to are likely to reduce or even offset the benefits of within-industry MNE spillovers. For instance, the possible loss of market shares of domestic firms to the advantage of MNEs may further increase firms' average cost curves, effectively reducing the efficiency of domestic firms. Both these contrasting mechanisms are at play in MNE intra-industry externalities, which contributes to explain why empirical analyses have recurrently found mixed results for horizontal spillovers (Crespo and Fontoura, 2007; Rojec and Knell, 2018).

Vertical spillovers, differently, refer to effects mediated through value chain relations. Following the seminal work of Javorcik (2004), spillovers are considered to diffuse through backward (i.e., from MNEs to domestic suppliers, upstream) and forward linkages (i.e., from MNEs to domestic costumers, downstream). These externalities are theoretically justified because value chain relations are crucial venues for cross-industry interactions among firms, particularly in the case of foreign and domestic ones (Barba Navaretti and Venables, 2006). Due to such vertical interdependencies, multinationals have increased incentives to provide knowledge and technological insights to their domestic counterparts. For instance, MNEs may require higher standards of quality and use inspections or share knowledge with their suppliers in order to obtain high-quality inputs. Spillovers through forward linkages may instead occur if MNE prices do not fully internalise the quality of the good and service provided to downstream domestic firms (e.g., for strategic reasons) (Resmini, 2019). Numerous contributions in the extant literature have highlighted the importance of vertical spillovers, particularly through backward linkages (Blalock and Simon, 2009; Beata S. Javorcik and Maggioni, 2017; Bitzer et al., 2008; Javorcik, 2004; Damijan et al., 2013).

Despite the substantial interest in multinationals across scientific fields, a number of questions have remained open. Two of these questions consider the role of MNEs as sources of knowledge spillovers across the industrial and geographical spaces.

More specifically, whereas the focus of the extant literature on MNE externalities has been on input-output linkages, conceptual reasons and empirical research suggest that those are not the only channels through which spillover occurs. Patent citations (Branstetter, 2006; Crescenzi et al., 2020), labour mobility (Poole, 2013; Csáfordi et al., 2020) and industrial relatedness (Lo Turco and Maggioni, 2019; Cortinovis et al., 2020) have also been investigated recently. From the perspective of a domestic firm, however, we only have limited evidence on these alternative channels and how they relate to the characteristics of recipient firms.

Besides, from a spatial point of view, it remains unclear what the geographical reach of MNE spillovers is. Although some indications in these respects have been provided (Halpern and Muraközy, 2007; Ivarsson and Alvstam, 2005), the literature indicates that the effect of MNEs is mostly intra-regional, and the diffusion of knowledge outside the region is essentially due to relations among domestic firms (Resmini, 2019). If taking a fine-grained and spatially-continuous perspective, do domestic firms geographically closer to MNEs benefit more from spillovers? Do different types of externalities (horizontal, vertical, relatedness) differ in their spatial reach? Given that strategic and location choices of MNEs have become increasingly intertwined (Beugelsdijk and Mudambi, 2013; Goerzen et al., 2013; Mudambi et al., 2018) and sub-national policy-makers strive for attracting foreign investments (Crescenzi et al., 2019; Crescenzi and Iammarino, 2017), it is crucial to acquire a deeper understanding on the spatial dimension of MNEs spillovers. To this end, we begin, in the following subsection, by providing a review of previous contributions on industrial relatedness and its potential role for MNE spillovers. After that, we discuss the literature on the spatial reach of MNE spillovers and how these are affected by distance and technology level. Based on our review of the extant literature, we put forward four testable hypotheses.

2.1 Industrial relatedness and MNE spillovers

Most of the empirical studies on MNE spillovers ignore the possibilities of capturing knowledge from related industries outside the value chain. This contrasts with the economic geography literature, which considers a broader set of dimensions through which industries might be connected. Various contributions in evolutionary economic geography have shown how cognitive proximity and more generally relatedness are important for the transmission of knowledge (Boschma, 2005; Content and Frenken, 2016; Hidalgo et al., 2018). The more related the knowledge and skill bases of different industries are, the easier it is for ideas, capabilities and knowledge to be profitably exchanged and applied. Thus, regardless of whether firms are suppliers or customers to each other, the similarity in technologies and skills, production processes or the goods and services provided opens up opportunities for knowledge diffusion.

The emerging literature of relatedness, spurred by Hidalgo et al. (2007), aims at studying these cognitive similarities. At the regional or national scale, empirical evidence consistently verifies the role of relatedness in facilitating knowledge spillovers and thus enhancing industrial diversification or economic development (Boschma and Frenken, 2011; Content and Frenken, 2016). Frenken et al. (2007) and Bishop and Gripaios (2010) found that regions with a higher degree of variety among related industries in a region is associated with high growth of regional employment. Neffke et al. (2011) and Xiao et al. (2018) found strong path dependencies in regions developing new industries that are technologically related to the pre-existing industries. The strong and consistent pattern linking spatial concentration of certain knowledge and activities and the probability of a region to enter into related fields of knowledge or economic activities has been put forward as the "principle of relatedness" (Hidalgo et al., 2018).

Recently, some scholars have examined cognitive proximity in relation to spillovers from foreign investments. For instance, Ascani et al. (2020) show that cognitively related external knowledge brought in through MNE networks positively affects regional innovation performance in Italy. Based on broader geographical settings, Cortinovis et al. (2020) cross-fertilise the literature on MNE externalities with the literature on industrial relatedness and show that MNEs presence in local related industries is positively associated with higher employment at the region-industry level in Europe. In the context of China, MNEs are shown to contribute to local diversification into less-related industries, arguably through the provision of new knowledge (Zhu et al., 2017).

Although these studies offer important contributions, their perspective is still relatively aggregate. Because aggregating preferences, choices and actions of micro-level agents may hide substantial heterogeneity, taking a more granular perspective would offer more insights. In the relatedness literature, micro-level dynamics have found relatively little space so far (Boschma, 2017), particularly in works on MNE spillovers. To the best of our knowledge, there are few closely related papers using firm-level data in developing economies. Using Turkish data, Lo Turco and Maggioni (2019) analysed the introduction of new products. They showed that related knowledge spilling from co-located MNEs fosters the introduction of product discoveries by domestic firms. Using Chinese data, Howell (2020) studied the relationship between industrial relatedness and firms' innovation process in response to the relaxation of foreign ownership controls. Their conclusion is that relatedness boosts innovation in every phase, with slight variations across different types of firms and the stage of innovation. Finally, the analysis by Szakálné Kanó et al. (2019) reports lower exit rates for Hungarian firms who are exposed to multinationals in related sectors.

In sum, the literature provides substantial evidence on the fact that multinationals, with their ability to control a network of subsidiaries and gather and use advanced knowledge and technologies from different locations (Mudambi et al., 2018), are important sources of knowledge spillovers (Crespo and Fontoura, 2007; Meyer and Sinani, 2009; Rojec and Knell, 2018). Industrial relatedness offers new perspectives on how such knowledge is diffused in the host economy, even outside of the standard supply chain linkages commonly used in the literature. At the same time, the role of relatedness as a channel for MNE spillovers and its impact at the micro level have found only limited attention. Building on previous contributions on relatedness (Lo Turco and Maggioni, 2019; Howell, 2020; Cortinovis et al., 2020) and productivity-enhancing MNE spillovers (Javorcik, 2004; Bitzer et al., 2008; Poole, 2013; Liang, 2017), we theorise that MNEs in a related industry may provide insights and knowledge beneficial to the productivity of domestic firms. Our first testable hypothesis is:

Hypothesis 1: Productivity of domestic firms is positively associated with the presence of multinational enterprises in related industries.

2.2 Spatial proximity and MNE spillovers

One of the objectives in this paper is to investigate comprehensively whether and how geographical proximity between multinational and domestic firms affects the generation and impact of spillovers. By focusing on the spatial dimension, we further combine the economic geography literature and international business literature by providing a micro distance-band analysis of MNE externalities.

In international business, scholars have predominately used country-level information as their primary geographic focus (Dunning, 1998, 2000; Zaheer, 1995; Buckley et al., 2007). Conversely, little attention has been paid to the sub-national context and the more fine-grained spatial heterogeneity, which is likely to drive the spatial concentration of knowledge, wealth and economic activities. These considerations have led to an urgent call for more research in integrating differences in spatial scales in international business research (Beugelsdijk and Mudambi, 2013; Mudambi et al., 2018). Recent research efforts have responded to such calls, for instance by empirically studying the interaction between MNE characteristics (strategic reason for FDI, subsidiary mandate, autonomy, etc.) and their sub-national location choices Goerzen et al. (2013); Geisler et al. (2018).

With respect to spillovers from multinationals, local characteristics are clearly crucial. On the one hand, they affect both the preferences of MNEs for sub-national locations (Beugelsdijk and Mudambi, 2013; Mudambi et al., 2018) and, thus, the availability itself of external knowledge (Crescenzi and Iammarino, 2017; Crescenzi et al., 2020). On the other hand, local characteristics are essential for the absorption of external knowledge (Crespo and Fontoura, 2007; Meyer and Sinani, 2009; Resmini, 2019). In this sense, contributions embedded in the economic geography literature pay closer attention to the spatial dimension of spillover effects (Resmini, 2019), although generally focusing on and finding support for intra-regional MNE spillovers (Girma and Wakelin, 2007; Bode et al., 2012).

With regard to horizontal spillovers, Aitken and Harrison (1999) studies domestic firms in Venezuela and found no evidence of local horizontal spillovers from MNEs, and Sjöholm (1999) found similarly insignificant results for horizontal spillover within regions in Indonesia. Lu et al. (2017) indicates that the domestic firms are more likely to benefit from horizontal FDI located nearby but to suffer from horizontal FDI located in more distant areas, confirming the positive agglomeration effects of FDI in China. Also in the US, horizontal spillovers are spatially localised, with effects mostly detected at metropolitan and state levels (Bode et al., 2012). When analysing spillovers from MNEs at different geographical scales in China, Liang (2017) reports no significant effect either for horizontal spillovers or for backward linkages, but some positive effects through forward linkages. Interestingly, the impact of spillovers from multinationals upstream is found to be larger at the provincial level than at the city level. Halpern and Muraközy (2007) is one of the few studies examining spillover effects weighted by spatial distance in comparison to the standard unweighted approach. Their results show that domestic firms close to foreign-owned firms benefit from positive horizontal spillovers, whereas backward MNE spillovers impact on productivity only at a national scale (unweighted variable). These results contrast with other studies, reporting technological (Ivarsson and Alvstam, 2005) and productivity improvements (Merlevede and Purice, 2016) in domestic suppliers located at a close distance from MNEs.

Our analysis of the empirical literature reveals that most studies focus on border discontinuities, whereas spatial distances are often neglected when investigating MNE spillovers. Although these choices are likely driven by data limitations, constraining spillover effects inside the administrative borders of regions offers at best a partial picture (Resmini, 2019). In these respects, our paper aims at dissecting the potential differential impacts of horizontal, vertical and relatedness spillovers with detailed distance bandwidth in a unified framework.

In building our hypothesis on spatial distance, there is only limited guidance with respect to horizontal and vertical effects, whereas no previous study considered relatedness spillovers from a spatial perspective. Besides, because most of the literature agrees on a more limited role of within-industry effects, we focus on cross-industry (i.e., vertical and relatedness) spillovers. We formulate our hypothesis on the basis of standard arguments in the economic geography literature. Our starting point is that knowledge is inherently sticky and, thus, has a strong spatial dimension (Breschi and Lissoni, 2001; Hidalgo et al., 2018). This implies that the spillovers are likely to exhibit some attenuation with distance (Audretsch and Feldman, 2004; Bottazzi and Peri, 2003) due to the fundamental role of face-to-face communication in facilitating the transmission of knowledge. As geographical distance increases, the opportunities for face-to-face interactions reduce, thus weakening the spillovers between geographically distant firms. Whether externalities materialise in the same industry (Bode et al., 2012), through vertical linkages (Javorcik, 2004), labour mobility (Poole, 2013) or patenting and alliances (Crescenzi et al., 2020), face-to-face interactions are likely to be important. Whereas knowledge at a closer *cognitive* distance is easier to transfer and may require fewer interactions (Frenken et al., 2007;

Boschma, 2005; Nooteboom et al., 2007), it is unclear whether relatedness spillovers are less sensitive to spatial decay. For these reasons, we hypothesise:

Hypothesis 2: Productivity of domestic firms is more strongly positively associated with the presence of multinational enterprises across industries at close distance.

2.3 Absorptive capacity and technological sophistication of domestic firms

A fundamental determinant of MNE spillovers is the technological sophistication of domestics firms. In line with the idea of cognitive distance (Boschma, 2005; Nooteboom et al., 2007) and broadly confirmed in the MNE literature (Kokko, 1994; Crespo and Fontoura, 2007; Alvarez and López, 2008; Perri and Peruffo, 2016), domestic firms having a large technological gap with MNEs are less likely to benefit from international exposure. In these respects, absorptive capacitymeasuring the stock of a firm's prior knowledgeis a crucial determinant of how well a firm can absorb and apply the new knowledge. Domestic firms with little absorptive capacity are also less likely to reap the MNE spillovers (Blalock and Simon, 2009; Fu et al., 2011; Liang, 2017).

Absorptive capacity is traditionally measured through R&D expenditures (Cohen and Levinthal, 1990; Zaheer, 1995). However, in the context of a developing country specialised in low-tech manufacturing such as Indonesia, this is unlikely to be appropriate. Whereas the relation between firm size and absorptive capacity is not clear cut (Zou et al., 2018), we opt to consider size as a proxy for capabilities and increased investment capacity in the Indonesia context and, therefore, related to absorptive capacity. Based on these considerations, we put forward the following hypothesis:

Hypothesis 3: The positive relation between spillovers from MNEs in the related industries and productivity of domestic firms is stronger for larger firms.

Studying MNE spillovers typically offers a daunting outlook for firms in low-tech industries because these industries are at the bottom of the distribution in terms of technological capabilities and absorptive capacity. Such a negative outlook may be particularly prominent for firms in industries hosting one or more MNEs because these domestic firms might eventually be crowded out of the market due to their inability to technologically upgrade and the direct competition from MNEs with superior technologies and products. With respect to value chain relations, it is unclear whether possible input-output connections between low- (e.g., basic components for computers) and high-tech (e.g. computers and sophisticated machinery) industries may contribute to technological upgrading. Besides, because the context of Indonesia is characterised mostly by low-tech firms, the incentives to share superior technology to domestic firms is minimal. However, industrial relatedness, different from the previous channels, seems to provide knowledge spillovers that are relatively easier to absorb. This could be a new but previously neglected path for low-tech firms to develop in the long run. If domestic firms aim to acquire new ideas, the best option may be to seek technologies and knowledge assets in related industries. Based on these arguments, we expect that:

Hypothesis 4: The positive relation between spillovers from MNEs in the related industries and productivity of domestic firms is stronger in low-tech industries.

3 Context: Indonesian Manufacturing Sectors

Indonesia provides an interesting avenue to study industrial relatedness in MNE spillovers on domestic firms over different spatial scales, and between low- and high-tech firms. It also enables us to test for the four mentioned hypotheses for two reasons. First, the availability of a rich data set from the annual census of manufacturing firms combined with a detailed input-output tables of 175 sectors. Second, the area is sufficiently large to capture the distance attenuation effect of MNE spillovers on domestic firms. The fact that the country is an archipelago with six relatively large islands where cities are located enables us to compare the results between cities in different islands. In this study, we focus mainly on the manufacturing sector because only panel data are available from this sector.

Indonesia comprises 27 provinces clustered into seven groups of islands with more than 300 districts. Then, a district receives its city (or *kota*) status when it fulfils the formal requirements from the central government, whereas the less-urbanised district is referred to as a regency (or *kabupaten*). It is interesting to note that two levels below a district, the area can be divided into an urbanised town (termed a *kelurahan* and village (or *desa*). Figure 1 shows the distribution of the urbanised town across different districts in Indonesia. The map also illustrates that urban areas are highly concentrated on Java island, followed by some districts in Sumatra and Sulawesi islands where manufacturing firms are mostly located. This distribution suggests that the concentration of manufacturing firms is correlated with the level of urbanisation or agglomeration. The manufacturing industries are heavily concentrated on Java, where more than three-quarters of medium and large manufacturing firms are located. Henderson and Kuncoro (1996) and Henderson et al. (1995) show that the concentration of manufacturing firms was the consequence of the economic liberalisation policies in the 1970s and 1980s, when firms took the opportunities to be located near to the central government offices.

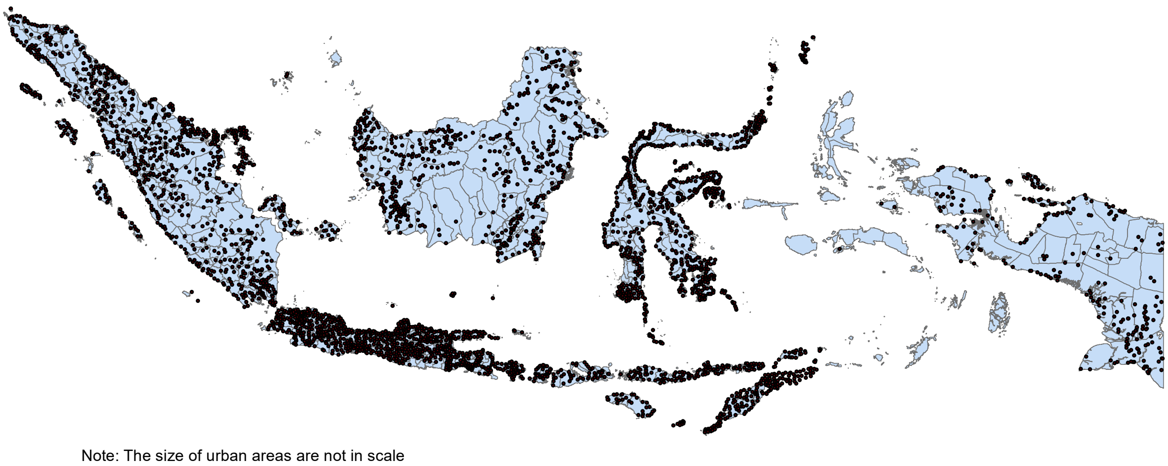


Figure 1: Distribution of urban areas in Indonesia. Administrative boundaries are shown by the solid line, where each dot represents the urbanised areas within a district.

During the 1990s and 2000s, the role of manufacturing industries increased substantially in Indonesia's economy, from 19% of GDP in 1990 to 24% in 2002 and 26% in 2009, although it declined due to the Asian economic crisis in 1997/98. When that crisis hit, the economy shrank by 13.3% and was followed by a decline in the manufacturing sector by 15%. After 1997, growth in the industrial sector was always below economic growth, leading to industrial sector growth only reaching 3.1% during 1997-2004.

The increase in industrial sectors can be traced back to the previous decade, particularly after the deregulation policies were carried out by the central government towards the industrial and foreign direct investment sectors (Blalock and Gertler, 2008). In 1967-1997, the industrial sector growth was almost always above growth in the economy. Economic growth in that period had an average of 6.1%, whereas growth in the industrial sector reached 10.3% per year. In those periods, various policies were carried out to increase industrial sector growth, including import substitution and export orientation.

Table 1 shows the shares of output for each 2-ISIC sector industry from 2002-2009. Industrial outputs are mainly concentrated in food, beverages and tobacco products followed by machinery, transport and equipment. Those two sectors combined account for more half of Indonesia's industrial output.

Industrial output does not reflect the industrial utilisation capacity rates during 2002-2009. The highest utilisation rate involved the paper industry and its products. Meanwhile, the industry that experienced high capacity utilisation growth was the shipping industry as the result of government regulations that encourage the sector to increase exports. On the other hand, the decline in capacity utilisation was experienced by the fertiliser, chemical and industrial sectors, particularly in 2008. The decline in capacity utilisation occurred due to the lack of supply of natural gas as a raw material and energy. The capacity utilisation rate also reflects the level of technology used by the manufacturing firms. This paper focuses on the heterogeneity between low- and high-tech firms.

From the export side, the coconut/palm oil processing; steel; machinery and automotive; textile; rubber processing; and electronics industries were the largest

Table 1: Share of output of 2-digit ISIC sector in total industry from 2002-2009 (%)

Manufacture Products	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Food, Beverages and Tobacco Products	32.0	31.4	29.7	28.6	28.5	29.8	30.4	33.2
Textiles and Wearing Apparel	13.9	13.8	13.0	12.4	12.1	10.6	9.2	9.2
Wood and Products of Wood	6.5	6.1	5.7	5.7	6.0	6.2	6.4	6.3
Paper and its Products	5.3	5.7	5.6	5.5	5.3	5.1	4.6	4.8
Coke, Refined Petroleum Products, Chemicals; Rubber and Plastics Products	10.9	11.6	11.6	12.3	12.6	12.5	13.5	12.8
Cement and Other Non-Metal Mineral Products	4.0	3.9	3.9	4.0	3.9	3.7	3.5	3.4
Basic Metals, Fabricated Metal Products	3.1	2.7	2.9	3.0	2.8	2.6	2.6	2.1
Machinery, Transport and Equipment	23.6	24.1	26.5	27.8	28.0	28.7	29.0	27.3
Others	0.8	0.9	0.9	0.9	1.0	0.9	0.8	0.8
Total	100	100	100	100	100	100	100	100

Source: Indonesia's Bureau of Statistics.

contributors to non-oil and gas exports. In general, non-oil and gas manufacturers tended to increase their exports, except in 2009, when lower demand existed from abroad due to the global financial crisis. Meanwhile, the steel; electronic, basic chemical; textile; and food and beverage industries were the biggest contributors to non-oil and gas import value. Furthermore, the non-oil and gas manufacturing industry during the last five years tended to increase imports.

4 Data & Methodology

4.1 Data

This study employs three primary data sources. The first primary data are Indonesia's medium and large manufacturing firms census (*Survei Industri Menengah dan Besar, IBS*) from 2002 to 2009. IBS are panel data collected yearly by Indonesia's Bureau of Statistics, BPS, that targets medium- (20-99 workers) and large-scale (above 100 workers) manufacturing firms. The IBS data provide rich information to study manufacturing firms productivity in which approximately 160 variables are collected every year. From the data, we know about the sectors with 5-digit ISIC, location, number of workers, capital, revenue, sales, intermediate inputs, production cost, type of firm (domestic or foreign) and export decision. Secondly, to link with the inter-industry externalities, we combine the IBS data with the input-output table from the year 2005 with 175 sectors. Lastly, we use the digital map of cities in Indonesia provided by the Geospatial Information Agency to construct the distances between cities.

4.2 Productivity Estimation

We would like to analyse the inter-industry externalities on firms' productivities by their total factor productivities (TFPs). The TFP is estimated by using the method from Wooldridge (2009) because it provides a simpler implementation in a generalised method of moments (GMM) framework to the moment conditions used by Levinsohn and Petrin (2003). Both methods are useful to control for the correlation between input levels and the unobserved firm-specific effects using intermediate inputs such as electricity or materials. With this approach, we can solve the simultaneity problem caused by the inputs using decisions and the increase in productivity.

The firm i's TFP at time t for each sector (2-digit ISIC) is estimated according to the following production function:

$$ln(y_{it}) = \alpha + \beta_1 ln(k_{it}) + \beta_2 ln(l_{it}) + \upsilon_{it} + \varepsilon_{it}, \tag{1}$$

where $ln(y_{it})$ is the firm's ouput, $ln(l_{it})$ the number of workers (input variable), and $ln(k_{it})$ the firm's capital (observed state variable). All variables are in logarithmic form. The unobserved productivity of a firm (υ_{it}) and the shocks (ε_{it}) are assumed to be independent of current and past inputs.

Table 2 shows the TFP estimation from equation 1 and other related variables with productivity measurement with different distances to be discussed in Section 4.

Table 3 shows that, in general, multinational firms (MNE) are more productive than the local firms. The average of total factor productivity of MNE is 6.100 versus

Table 2: Descriptive statistics of TFP estimates and other related variables

VARIABLES	N	mean	sd	min	max
TFPW	109,955	4.578	1.232	0.308	13.47
HMNE	174,404	0.0854	0.187	0	1.000
H30MNE	113,103	0.132	0.225	0	1
H60MNE	151,434	0.157	0.226	0	1
H90MNE	147,697	0.187	0.266	0	1
H120MNE	148,446	0.148	0.212	0	1
H150MNE	133,461	0.109	0.203	0	1
H151MNE	171,958	0.185	0.174	0	1
RMNE	174,398	0.0589	0.0761	0	0.575
R30MNE	172,548	0.0637	0.0856	0	0.575
R60MNE	173,622	0.114	0.107	0	0.597
R90MNE	173,430	0.109	0.0931	0	0.533
R120MNE	173,849	0.104	0.0988	0	0.583
R150MNE	173,658	0.0563	0.0700	0	0.498
R151MNE	173,980	0.195	0.0719	0	0.516
BMNE	174,321	0.0620	0.119	0	1
B30MNE	172,545	0.0693	0.128	0	1
B60MNE	173,619	0.114	0.159	0	1
B90MNE	173,427	0.123	0.172	0	1
B120MNE	173,846	0.112	0.156	0	1
B150MNE	173,655	0.0550	0.116	0	1
B151MNE	173,977	0.203	0.156	0	0.982
FMNE	174,321	0.0539	0.133	0	0.967
F30MNE	172,545	0.0624	0.139	0	0.954
F60MNE	173,619	0.103	0.178	0	0.958
F90MNE	173,427	0.105	0.182	0	0.969
F120MNE	173,846	0.106	0.177	0	0.967
F150MNE	173,655	0.0425	0.0943	0	0.961
F151MNE	173,977	0.204	0.172	0	0.966
Export Share	174,404	0.0890	0.264	0	1.000
HI	174,404	0.360	0.307	0.00386	1
Bckw Output (log)	174,321	9.714	5.160	0	19.23

4.580 for local firms. MNEs are also larger, with an employment mean of 559.360, whereas local firms average number of workers is 150.920. Finally, multinational firms are more likely to export, with an export share of their total products of 28.8% compared to 8.9% for those local firms.

Table 3: Local firms and MNEs in Indonesia

	Domestic	MNEs
TFP	4.580	6.100
Employment	150.920	559.360
Export Share	8.900	28.800

Note: Figures are the mean values for selected variables

4.3 Relatedness Measure

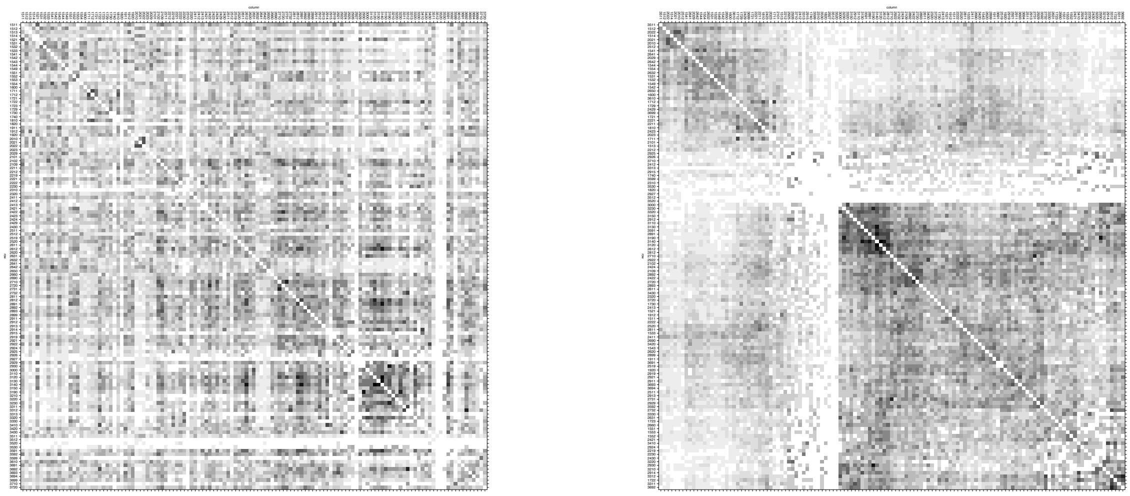
Following the seminal work of Javorcik (2004), researchers studying spillover effects of MNEs have customarily focused on input-output linkages. Although such relations are well-justified channels for productivity-enhancing effects, spillovers are unlikely to be confined to value chain linkages. Because industries can be related to each other above and beyond buyer-supplier relations, we follow the burgeoning literature on relatedness in economic geography (Boschma and Capone, 2015; Hidalgo et al., 2018; Cortinovis et al., 2020) and use industrial relatedness to capture possible MNE spillovers.

Empirically, our relatedness measure follows the methodology proposed by Hidalgo et al. (2007). Intuitively, this method relies on the systematic co-occurrence of specialisations in the same area to capture the proximity between industry pairs. When specialisations in any two industries occur frequently (i.e., in many areas), the two sectors are considered to be related. The factors driving such relatedness are not revealed but can be theoretically linked to similarity in skills, technology and inputs (Hidalgo et al., 2007). In more formal terms, to estimate industrial relatedness in Indonesia, we proceeded as follows.

First, using data from the Indonesian manufacturing census of 2002, we aggregate plant-level employment data to the industry-city level and compute location quotients.

$$LQ_{c,s} = \frac{E_{c,i} / \sum_s E_{c,s}}{\sum_c E_{c,s} / \sum_{c,s} E_{c,s}} \tag{2}$$

In the equation above, $E_{c,s}$ represents the number of workers in city c in industry i. The nominator of the fraction measures the share of workers in industry s over the total employment in c, whereas the denominator captures the share of workers in industry s in the country over total employment. As is customary in the literature, we take values of $LQ_{c,s}$ greater than 1 as implying that city c is relatively specialised in industry s compared to the rest of the country. We then make the location quotient scores a binary variable to capture industrial specialisations across cities:



(a) Sorted by ISIC code (b) Sorted by hierarchical clustering

Figure 2: Relatedness scores ϕ

$$S_{c,s} = \begin{cases} 1 & \text{if } LQ_{c,s} > 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Second, we study the pattern of co-occurrence of specialisation to define relatedness.

$$\phi_{s,r} = min\{P(S_{c,s}|S_{c,r}), P(S_{c,r}|S_{c,s})\} \tag{4}$$

Specifically, the relatedness score (ϕ) is computed as the minimum between the probability of being specialised in s conditional on being specialised in r (first term of the min function) and the probability of being specialised in r conditional on being specialised in s (the second term). In this way, we obtain an industry-by-industry matrix with values ranging between 0 and 1 capturing the intensity of relatedness between each pair of industries.

The relatedness matrix is represented graphically in Figure 2, in which darker cells in the matrix indicate higher relatedness scores. The first panel (a) shows the matrix arranged by ISIC code, with code 1511 (Processed meat) on the first row and column and code 3720 (Recycling of non-metal waste) on the last. Higher scores of ϕ appear closer to lower right-hand corner of the matrix. This pattern suggests that "higher" ISIC codes tend to score higher in terms of relatedness. Panel b of Figure 2 reproduces the same matrix, the rows and columns of which have been arranged by a clustering algorithm. Similar to the original contribution of Hidalgo et al. (2007), our relatedness matrix has a modular structure. A large cluster, encompassing slightly more than half of industries, is isolated in the bottom right corner of the figure. Besides, some industries are shown as poorly connected to the rest of the network (light-coloured rows/columns).

Figure 3 offers some clearer indication on our relatedness matrix. In the figure, industries are plotted as nodes of a network, and their relative position provides an indication of the proximity between two nodes. The number reported in each node refers to the first two digits of the ISIC code, whereas the colour and shape of the nodes refer, respectively, to broader industry groupings and the level of knowledge-intensity of the industry. Interestingly, advanced industries (squares) are almost exclusively concentrated in the top left corner of the graph (8 our of 9), suggesting high levels of relatedness among them. For instance, our graph suggests that sectors producing machinery and equipment (29), electrical machinery (31) and medical and precision tools are closely related. In this sense, a domestic firm in sector 29 is more likely to benefit from MNE spillovers when the MNE operates in sector 31 rather than in sector 15 (Food and beverage). This observation is in line with panel a of Figure 2 because most knowledge-intensive industries tend to have a high ISIC code. Besides, approximately one third of the 36 industries with medium-high knowledge intensity (triangles) are also proximate to the square nodes. Finally, the colouring and numbering of the nodes also reveal a clearly non-random pattern, in which industries with the same 2-digit code or colour tend to be close to each other.

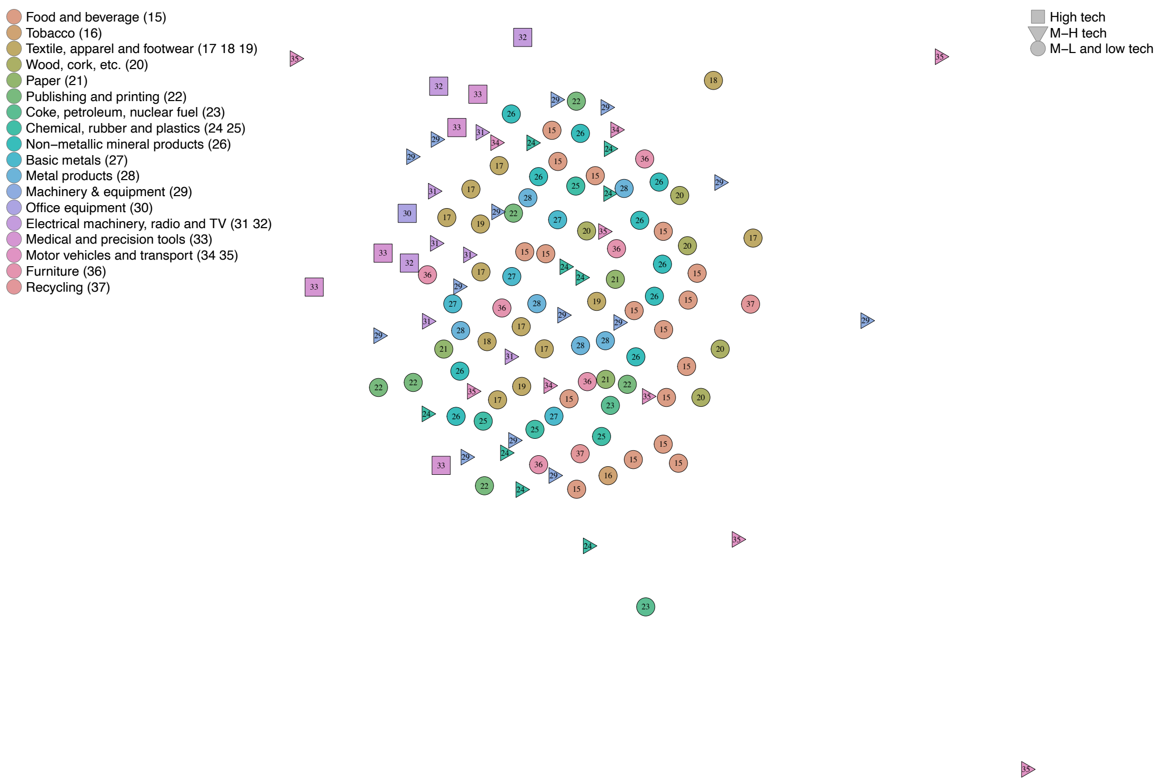


Figure 3: Relatedness network

4.4 Modelling

The main objective of our work is to investigate the role of industrial relatedness as a channel for productivity-enhancing MNE spillovers and explore the spatial reach of such effects.

To this aim, we exploit the information from the Indonesian manufacturing census to assess whether the presence of multinationals across the geographical and industrial space affects productivity of indigenous firms. In a standard panel data framework, our baseline regression can be written as follows:

$$lnTFP_{i,s,c,t} = \beta * HMNE_{s,c,t-1} + \gamma * RMNE_{s,c,t-1} + \delta * controls_{s,c,t-1} + \omega_i + \sigma_s + \tau_{c,t} + \epsilon_{i,s,c,t}, \tag{5}$$

In equation 5, we regress firm i's total factor productivity on various measures of spillover intensity, both within the same sector ($HMNE$) as well as in related industries ($RMNE$). In our baseline, our variables of interest (and also most of the controls) vary at 4-digit sector (s), city (c) and year (t) levels. Our model also includes firm (ω_i), sector (σ_s) and city-year ($\tau_{c,t}$) fixed effects.

4.5 Spillover measures and spatial scale

To measure the intensity of spillover effects to which domestic firms are exposed, we follow the method firstly introduced by Javorcik (2004). First, we compute the $HMNE$ as the ratio of real output ($outpr_{i,s,c,t}$) of MNEs (weighted by the share of foreign-ownership ($f_{i,s,c,t}$) over the total real output in sector, city and year group. In more formal terms:

$$HMNE_{s,c,t} = \frac{outpr_{i,s,c,t} * f_{i,s,c,t}}{\sum_i outpr_{i,s,c,t}} \tag{6}$$

To derive the measure of spillovers from related industries for industry s, we weight and sum $hMNE_{r \neq s,c,t}$ by the pairwise relatedness score. Formally:

$$RMNE_{s,c,t} = \sum_{r \text{ if } r \neq s} HMNE_{r,c,t} * \phi_{r,s} \tag{7}$$

We use the same approach as in Equation 7 to compute a measure of backward spillovers ($BMNE$)[1], which we include as a control variable. In the case of spillovers through backward linkages, the weighting factor is given by the share of output of sector s supplied to sector r.

Besides studying the relation between MNE spillovers and domestic productivity, our paper aims at shedding some light on the spatial scale of relatedness-mediated spillover. To this end, we compute the pairwise distance between each of the cities in our sample and calculate our spillover measures in different concentric and mutually-exclusive rings at varying levels of distance from each city (respectively, 30, 60, 90, 120, 150 and above 150 km from the focal city c). For example, MNE spillovers in related industries within 30 km are computed as follows:

$$R30MNE_{s,c,t} = \begin{cases} \sum_{r \text{ if } r \neq s} HMNE_{r,m,t} * \phi_{r,s} & \text{if } d_{c,m} \leqslant 30\text{km} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

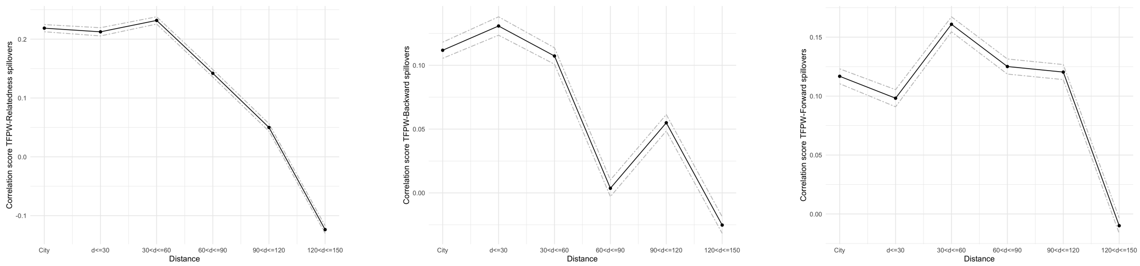
In the equation above (8), spillovers from related industries are computed as before but only including cities other than c but within 30 km from c. For the second ring ($R60MNE_{s,c,t}$), we include cities beyond 30 km and up to 60 km. We repeat the operation at different spatial scales (up to 150 km and beyond) and for different variables ($HMNE$, $RMNE$, $BMNE$). In this way, we can progressively saturate the model with MNE spillover variables at different distances to explore their spatial reach of various MNE spillovers. The descriptive statistics of these distance-related spillovers are shown in Table 2.

5 Results

As a preliminary step in our econometric analysis, we study the correlation patterns between productivity levels of Indonesian firms and exposure to MNE via relatedness, backward and forward linkages. Figure 4 provides a graphical overview of those patterns. The correlation between the productivity of a firm and exposure to MNE spillovers decays over space in all three graphs, although with different

[1]We also compute forward spillovers ($FMNE$) for our robustness checks.

patterns. The correlation between relatedness-mediated spillovers and TFP peaks at 60 km before gradually decaying, even becoming negative for the highest distance group. Interestingly, relatedness spillovers show the highest correlation to TFP at short distance (roughly double compared to the other two) but the lowest as the distance increases. Differently, the spatial reach of spillovers through backward linkages seems the most limited because the correlation peaks at 30 km and rapidly approaches zero thereafter. Finally, spillovers mediated by forward linkages are roughly equally correlated to TFP at a short distance and up to 120 km.



(a) Relatedness (b) Backward linkages (c) Forward linkages

Figure 4: Correlation scores between local TFP and MNE spillovers at different distances

5.1 Main results

The graphical representation of bivariate correlation scores offers some informative *prima facie* insights concerning the spatial decay pattern of MNE spillovers. To further investigate the spatial reach of MNE spillovers through different channels through panel regressions.

We begin by focusing on each channel and regressing the level of productivity of domestic firms on MNE spillovers between 0 and 150+ km. The results are reported in Table 4. The odd-numbered columns focus on spillovers at "short distance", whereas the even-numbered columns also include medium and long distances, thus encompassing all the different spatial rings we computed. For ease of interpretation, the column "Reach" shows the distance categories within which we classified the spillover measures. We consider distances up to 60 km as short, between 61 and 120 km as medium and above 121 as long distance. Considering short distance for MNE spillovers at up to 60 km appears justified because the daily commuting patterns around Jakarta are on average over 20 km (Sofiyandi and Siregar, 2020), and about a third of Indonesians commute to work for more than 30 km (Arifin and Ananta, 2017) at the national level.

Horizontal spillovers (Columns 1 and 2) are negatively associated with domestic firms' productivity inside the same municipality ($SpillMNE$) but revert to a positive significant relation after more than 150 km (($Spill150+MNE$)). Spillover effects mediated by relatedness (Columns 3 and 4) are instead positive and significant only at short distance, specifically between 31 and 60 km from the municipality of the focal firm. Relatedness-mediated spillovers appear to be both large in size and in significance, although less spatially encompassing than expected. Our findings on relatedness-mediated spillovers and their coefficients' size are roughly in line with Figure 4. The same, however, does not apply to spillovers through backward linkages. In the plotted correlations, this channel seems to have a rather short spatial reach. In our regressions (Columns 5 and 6), MNE spillovers from upstream industries are positively associated with at short ($Spill60MNE$) as well as longer ($Spill120MNE$) distances. Finally, as most of the extant literature suggests, spillovers through forward linkages (Columns 7 and 8) are almost exclusively insignificant.

With respect to our hypotheses, the results of Column 3 and 4 offer some indications supportive of Hypothesis 1. Specifically, we had theorised that exposure to MNEs' activities through related industries would have a positive effect on domestic firms' productivity (Hypothesis 1). Although not occurring at each and every one of our distance bands, the positive coefficient for relatedness-mediated spillovers between 31 and 60 km offers some support to our reasoning. These results are also in line with Hypothesis 2, which theorised a spatial decaying pattern in MNE spillovers. In these respects, relatedness-mediated spillovers occur at short distance (between 31 and 60 km) from the focal municipality but are undetected at large distances. Hypothesis 2 also finds some confirmation for backward linkages because these are found to be positively and significantly associated with domestic firms' productivity at short (between 31 and 60 km) and medium (between 91 and 120 km) distances, while turning insignificant for long distances. Finally, Hypothesis 2 is rejected for spillovers through forward linkages because these are essentially insignificant at any spatial scale.

Table 4: MNE spillovers in Indonesia

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Reach	Horizontal	Horizontal	Relatedness	Relatedness	Backward	Backward	Forward	Forward
SpillMNE	Short	-0.0549*	-0.0767*	0.316	0.306	0.028	0.0201	-0.0118	-0.00241
		(0.0322)	(0.0396)	(0.296)	(0.304)	(0.0376)	(0.0375)	(0.0427)	(0.0433)
Spill30MNE	Short	-0.0137	-0.0343	-0.1	-0.13	-0.0113	-0.0121	-0.0128	0.00164
		(0.0218)	(0.0273)	(0.287)	(0.294)	(0.0405)	(0.0405)	(0.0486)	(0.0523)
Spill60MNE	Short	-0.011	-0.0202	0.552***	0.549**	0.0736**	0.0713**	-0.0234	-0.0184
		(0.0238)	(0.0264)	(0.210)	(0.219)	(0.0347)	(0.0351)	(0.0386)	(0.0383)
Spill90MNE	Medium		-0.0239		-0.00413		0.0303		-0.0296
			(0.0226)		(0.243)		(0.0239)		(0.0342)
Spill120MNE	Medium		0.0343		-0.0928		0.0795**		-0.0466
			(0.0328)		(0.213)		(0.0357)		(0.0372)
Spill150MNE	Long		-0.0111		-0.196		0.03		-0.031
			(0.0287)		(0.312)		(0.0381)		(0.048)
Spill150+MNE	Long		0.0926*		0.164		-0.028		-0.0916***
			(0.0498)		(0.1980)		(0.0388)		(0.032)
Export (log)		0.00255**	0.00252	0.00273***	0.00274***	0.00273***	0.00274***	0.00274***	0.00273***
		(0.0013)	(0.0016)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
HI 2 digit		-0.0325	-0.0345	-0.014	-0.0146	-0.0127	-0.0112	-0.0128	-0.0128
		(0.0296)	(0.035)	(0.0218)	(0.0218)	(0.0218)	(0.0219)	(0.0218)	(0.0217)
Bckw Output (log)		-0.00131	-0.00345	0.000606	0.000558	0.000308	0.000312	0.000804	0.000815
		(0.0019)	(0.0023)	(0.00158)	(0.00157)	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Observations		47,711	37,828	80,682	80,664	80,683	80,665	80,683	80,665
R-squared		0.913	0.915	0.903	0.903	0.903	0.903	0.903	0.903
City Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISIC5 Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Our preliminary analysis on the spatial extent of MNE spillovers suggests that such spillovers are subject to spatial decay, even though not in each and every one of our distance bands. In the second step of the analysis, we focus on short and medium distance spillovers through the four possible channels we identified. This approach allows us to study MNE spillovers in more realistic settings and control for possible correlations between spillover measures. The results are reported in Table 5. In our analysis, we also explore possible sources of heterogeneity in our results by estimating our models for small and medium (Column 5) and large (Column 6) firms separately. The reason behind this choice is to indirectly examine possible differences in absorptive capacity (Hypothesis 3). Because our data do not provide reliable information on human capital and knowledge assets of firms, we exploit the fact that bigger firms are likely better able to absorb external knowledge, also thanks to possible complementary capabilities (Blalock and Simon, 2009). Similarly, we use industry codes to investigate whether technological sophistication influences the impact of MNE spillovers (Hypothesis 4). Domestic firms in more advanced industries may be more committed or better able to capture MNE spillover effects, for instance because of improved cognitive proximity (cf. Figure 3). On the other hand, MNEs in advanced industries may be particularly careful in preventing knowledge leakage. We explore the relation between sophistication and MNE spillovers and test Hypothesis 4 in Columns 7 (industries of low and medium-low technology) and 8 (industries of high and medium-high technology).

The main findings discussed in relation to Table 4 and their indications concerning Hypotheses 1 and 2 are confirmed in Table 5. Horizontal spillovers from multinationals appear to matter at very close distance ($HMNE$), and, interestingly, they are the only one for which we find evidence of any within-municipality effect. Spillovers from either relatedness or input-output linkages are not significant either within the municipality or within a radius of up to 30 km from the city centroid. However, once the radius is extended up to 60 km, the spillover effects through relatedness ($R60MNE$) and backward linkages ($B60MNE$) both turn positive and highly significant. This result suggests that multinationals do provide some beneficial effect on the productivity of domestic manufacturing firms when located in proximity. Adding spillovers at up to 90 km distance does not affect this result.

We further explore possible heterogeneity in this finding by examining specific subsamples of our data. In column 5, we restrict the analysis to domestic firms in the three lower quartiles of the employment distribution of each industry, whereas in column 6, we analyse the top quartile. Because larger firms are likely to possess increased absorptive capacity, we expect them to particularly benefit from MNE spillover effects. The comparison of the results in Column 5 and 6 supports our intuition and confirms Hypothesis 3. Besides, our model suggests that larger firms may benefit from MNE presence even when they are further away. Specifically, whereas small and medium firms benefit from spillovers at a closer range ($RMNE60$), the productivity of larger firms is positively associated with spillovers through relatedness at distances of up to both 60 and 90 km ($RMNE60$, $RMNE90$). Interestingly, the magnitude of the coefficient also varies with firm size: the strength of relatedness spillovers in the top quartile of the sectoral employment distribution is almost double ($RMNE60$ in Column 6) compared to the average picture ($RMNE60$ in Column 4). In columns 7 and 8, we split the sample based on the knowledge intensity of the sector to which a firm belongs. About 3 in 4 firms in our data belong to the low-tech industries (Column 7). This group of firms appears to be negatively affected by horizontal spillovers at close distance ($HMNE$ and $HMNE30$) but profits from cross-industry spillovers at larger distances ($BMNE60$, $BMNE90$, $RMNE60$). Firms in more knowledge-intensive industries instead are largely unaffected by MNEs, with the exception of horizontal (negative coefficient) and relatedness-mediated (positive and significant coefficient) spillovers between 31 and 60 km. Because both firms in low- and high-tech industries overall benefit from MNE externalities (between 31 and 60 km), we reject hypothesis 4.

Previous contributions have mostly focused on MNE spillovers through input-output relations and without paying much attention to the role of spatial distance. The results in the extant literature are rather mixed, with spillover effects mostly found at close distance. Our results, in these respects, are different. We find little evidence of effects of MNE spillovers within Indonesian municipalities, and any that we do find is mostly confined to productivity-reducing horizontal spillovers. However, outside the city boundaries (Hypothesis 2, confirmed), and particularly between 30 and 60 km, the presence of MNEs generates TFP-enhancing externalities in related industries (Hypothesis 1, confirmed). Besides, our result suggests that larger firms are able to better "source" and absorb spillovers from MNEs in related industries (Hypothesis 3, confirmed) and at increased distances (up to 90 km) than other firms. Finally, technological sophistication does not seem to be associated with spillovers (Hypotheses 4, rejected).

Table 5: MNE spillovers in Indonesia in a unified framework

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	TFPWME	TFPWME	TFPWME	TFPWME	TFPWME - SM	TFPWME - L	TFPWME - Low	TFPWME - High
HMNE	-0.0466*	-0.0509*	-0.0526*	-0.0513*	-0.0490	-0.0881*	-0.0887**	0.0160
	(0.0269)	(0.0271)	(0.0272)	(0.0271)	(0.0307)	(0.0490)	(0.0344)	(0.0488)
RMNE	0.348	0.320	0.230	0.252	0.154	-0.511	0.343	0.137
	(0.291)	(0.305)	(0.307)	(0.308)	(0.342)	(0.581)	(0.379)	(0.563)
BMNE	0.0295	0.0258	0.0262	0.0219	0.0352	0.0558	0.0293	-0.0450
	(0.0383)	(0.0382)	(0.0378)	(0.0371)	(0.0487)	(0.0735)	(0.0405)	(0.106)
FMNE	-0.00519	-0.0110	-0.0107	-0.00168	0.00138	-0.109	-0.00110	-0.142
	(0.0424)	(0.0429)	(0.0420)	(0.0433)	(0.0531)	(0.0719)	(0.0475)	(0.124)
H30MNE		-0.0179	-0.0250	-0.0246	-0.0294	-0.0272	-0.0449*	0.00585
		(0.0206)	(0.0208)	(0.0209)	(0.0254)	(0.0407)	(0.0251)	(0.0408)
R30MNE		0.0422	-0.215	-0.229	-0.289	-0.742	-0.0144	-0.509
		(0.266)	(0.295)	(0.298)	(0.329)	(0.714)	(0.361)	(0.582)
B30MNE		-0.00619	-0.00894	-0.0127	0.0220	-0.00688	-0.00286	0.0108
		(0.0404)	(0.0404)	(0.0404)	(0.0489)	(0.0849)	(0.0429)	(0.147)
F30MNE		-0.0114	-0.0151	-0.00572	0.0191	-0.1000	-0.0519	0.183
		(0.0484)	(0.0489)	(0.0519)	(0.0701)	(0.0823)	(0.0544)	(0.136)
H60MNE			-0.00731	-0.00815	0.0186	-0.0478	0.0235	-0.0844**
			(0.0207)	(0.0209)	(0.0247)	(0.0380)	(0.0237)	(0.0396)
R60MNE			0.654***	0.632***	0.659***	1.129**	0.773***	0.929*
			(0.213)	(0.216)	(0.240)	(0.484)	(0.260)	(0.483)
B60MNE			0.0725**	0.0717**	0.0606	0.0761	0.0676*	0.146
			(0.0348)	(0.0349)	(0.0416)	(0.0657)	(0.0403)	(0.102)
F60MNE			-0.0302	-0.0263	-0.0309	-0.0958	-0.00688	-0.0844
			(0.0387)	(0.0389)	(0.0495)	(0.0835)	(0.0421)	(0.108)
H90MNE				0.0108	0.0205	-0.0553	0.00957	0.00929
				(0.0160)	(0.0182)	(0.0354)	(0.0192)	(0.0356)
R90MNE				0.0874	-0.289	1.026**	0.119	-0.515
				(0.252)	(0.287)	(0.487)	(0.299)	(0.493)
B90MNE				0.0290	0.0316	-0.0687	0.0439*	-0.0822
				(0.0240)	(0.0289)	(0.0540)	(0.0253)	(0.0764)
F90MNE				-0.0332	-0.0282	-0.0486	-0.0156	-0.00774
				(0.0337)	(0.0421)	(0.0525)	(0.0357)	(0.0952)
Export (log)	0.00264***	0.00263***	0.00259***	0.00259**	0.00167	0.000702	0.00285**	0.00260
	(0.000994)	(0.00101)	(0.00100)	(0.00100)	(0.00152)	(0.00142)	(0.00114)	(0.00221)
HI 2 digit	-0.0186	-0.0116	-0.0118	-0.0117	-0.00426	-0.0132	0.000348	0.00833
	(0.0218)	(0.0219)	(0.0219)	(0.0219)	(0.0267)	(0.0492)	(0.0272)	(0.0447)
Bckw Output (log)	0.000642	0.000572	0.000190	0.000152	-0.000319	0.00391	-0.000535	0.00161
	(0.00158)	(0.00161)	(0.00161)	(0.00160)	(0.00192)	(0.00353)	(0.00187)	(0.00337)
Observations	81,264	80,427	80,402	80,382	59,357	18,172	58,846	20,656
R-squared	0.903	0.904	0.904	0.904	0.901	0.921	0.900	0.924
City Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISIC5 Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.2 Robustness checks

To test the validity of our results, we perform a number of robustness checks. First, we consider whether using employment rather than output to capture MNE spillovers may change the results. The results reported in Table 6 are very well in line with our findings. Two main interesting aspects slightly differing from our previous results should be highlighted. First, horizontal spillovers are mostly insignificant within the city boundaries. Besides, we find negative coefficients from horizontal spillovers only in the case of small and medium firms and firms in low-tech industries. Second, the positive relation between spillovers through backward linkages and productivity pertains to large firms and firms in high-tech industries. Both these points suggest that there may be relevant implications in the choice of how to measure MNE spillover effects, even though the use of both output and employment is theoretically justified (Javorcik, 2004; Poole, 2013).

Our second set of robustness checks consider two possible alternative choices of our dependent variable (Table 7): total factor productivity computed following Levinshon and Petrin's method (Levinsohn and Petrin, 2003) and a basic measure of labour productivity (Output per employee). The results are largely confirmed when using a different method for estimating total factor productivity, whereas some of the significant effects found previously disappear in the case of labour productivity. It should be stressed that this measure of productivity, in contrast to previous ones, does not control for differences in the capital endowment of firms and endogenous choices of firms with respect to the use of capital and labour. This point is important because increased capital investments are associated with higher technological sophistication and absorptive capacity, and, in turn, with the ability to capture knowledge spillovers. In line with this reasoning, we notice that the $R60MNE$ is positive and significant for larger firms (Column 8).

Our final set of robustness checks consider two further aspects: possible firm exit and attrition issues in our panel and possible differences due to the geography of Indonesia. With respect to the first aspect, we estimate our model only using firms that we can observe throughout the period (Columns 1 to 5, marked with "NoEx"). The exclusion of firms dropping out from the panel does not affect our conclusions.

Table 6: MNE spillovers in Indonesia (Employment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	TFPWME	TFPWME	TFPWME	TFPWME	TFPWME - SM	TFPWME - L	TFPWME - Low	TFPWME - High
HMNE-E	0.00474	-0.000593	-0.00389	-0.00432	0.000850	0.00128	-0.0612	0.0837
	(0.0334)	(0.0341)	(0.0340)	(0.0341)	(0.0392)	(0.0629)	(0.0412)	(0.0631)
RMNE-E	0.382	0.388	0.256	0.273	0.128	-0.477	0.564	-0.0743
	(0.335)	(0.351)	(0.352)	(0.352)	(0.388)	(0.661)	(0.445)	(0.611)
BMNE-E	0.0229	0.0206	0.0245	0.0230	0.0496	0.0530	0.0324	-0.0948
	(0.0412)	(0.0410)	(0.0407)	(0.0404)	(0.0546)	(0.0806)	(0.0430)	(0.127)
FMNE-E	-0.00516	-0.0108	-0.00676	-0.00212	-0.0157	-0.0637	0.00726	-0.165
	(0.0447)	(0.0454)	(0.0447)	(0.0459)	(0.0586)	(0.0735)	(0.0494)	(0.130)
H30MNE-E		-0.0306	-0.0394	-0.0386	-0.0754**	0.0159	-0.0764**	0.00343
		(0.0270)	(0.0270)	(0.0272)	(0.0338)	(0.0468)	(0.0328)	(0.0494)
R30MNE-E		-0.0423	-0.392	-0.406	-0.484	-0.842	-0.282	-0.464
		(0.290)	(0.328)	(0.329)	(0.374)	(0.808)	(0.391)	(0.650)
B30MNE-E		-0.00291	-0.00451	-0.00484	0.0162	0.0651	-0.00794	0.0193
		(0.0464)	(0.0465)	(0.0466)	(0.0574)	(0.102)	(0.0511)	(0.149)
F30MNE-E		-0.00499	0.000285	0.00178	0.0298	-0.0914	-0.0298	0.157
		(0.0500)	(0.0506)	(0.0529)	(0.0717)	(0.0780)	(0.0582)	(0.157)
H60MNE-E			-0.0129	-0.0139	0.0105	-0.0333	0.0301	-0.119**
			(0.0292)	(0.0290)	(0.0354)	(0.0512)	(0.0336)	(0.0548)
R60MNE-E			0.793***	0.772***	0.936***	0.996*	0.698**	1.488***
			(0.254)	(0.262)	(0.290)	(0.592)	(0.319)	(0.565)
B60MNE-E			0.0598	0.0646*	0.0303	0.131*	0.0436	0.269**
			(0.0375)	(0.0373)	(0.0440)	(0.0747)	(0.0413)	(0.134)
F60MNE-E			-0.0478	-0.0445	-0.0375	-0.138	-0.0438	-0.0222
			(0.0410)	(0.0414)	(0.0540)	(0.0906)	(0.0445)	(0.155)
H90MNE-E				0.0101	0.0115	-0.0522	0.00980	0.0126
				(0.0185)	(0.0214)	(0.0406)	(0.0226)	(0.0422)
R90MNE-E				0.0507	-0.339	1.206**	0.116	-0.788
				(0.270)	(0.308)	(0.509)	(0.320)	(0.545)
B90MNE-E				-0.0134	-0.0209	-0.107**	0.0107	-0.138
				(0.0284)	(0.0342)	(0.0545)	(0.0307)	(0.0956)
F90MNE-E				-0.0300	-0.0136	-0.0736	-0.0177	-0.0239
				(0.0358)	(0.0468)	(0.0580)	(0.0379)	(0.114)
Export (log)	0.00264***	0.00264***	0.00259**	0.00257**	0.00165	0.000581	0.00282**	0.00275
	(0.000994)	(0.00101)	(0.00100)	(0.00101)	(0.00153)	(0.00143)	(0.00114)	(0.00221)
HI 2 digit	-0.0174	-0.0104	-0.0109	-0.0109	-0.00414	-0.0119	0.00138	0.0103
	(0.0217)	(0.0218)	(0.0218)	(0.0218)	(0.0267)	(0.0493)	(0.0272)	(0.0451)
Bckw Output (log)	0.000750	0.000659	0.000344	0.000454	1.79e-05	0.00386	-0.000269	0.00196
	(0.00159)	(0.00163)	(0.00163)	(0.00163)	(0.00193)	(0.00350)	(0.00191)	(0.00346)
Observations	81,264	80,427	80,402	80,382	59,357	18,172	58,846	20,656
R-squared	0.903	0.904	0.904	0.904	0.901	0.921	0.900	0.924
City Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISIC5 Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Alternative dependent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TFPME	TFPME - SM	TFPME - L	TFPME - Low	TFPME - High	Lab. Prod.	Lab. Prod. - SM	Lab. Prod. - L	Lab. Prod. - Low	Lab. Prod. - High
HMNE	-0.0529*	-0.0514	-0.0845*	-0.0882**	0.0184	-0.0340	-0.0358	-0.0361	-0.0417	-0.0162
	(0.0276)	(0.0315)	(0.0483)	(0.0348)	(0.0496)	(0.0242)	(0.0294)	(0.0429)	(0.0304)	(0.0425)
RMNE	0.179	0.0340	-0.510	0.294	0.0746	0.238	0.161	0.0725	0.386	-0.395
	(0.308)	(0.348)	(0.562)	(0.383)	(0.555)	(0.268)	(0.332)	(0.393)	(0.331)	(0.522)
BMNE	0.0190	0.0206	0.0787	0.0213	-0.0237	0.0251	0.0556	0.00889	0.0244	0.0750
	(0.0370)	(0.0492)	(0.0752)	(0.0407)	(0.104)	(0.0388)	(0.0518)	(0.0546)	(0.0436)	(0.0892)
FMNE	-0.00633	-0.00122	-0.0986	-0.00502	-0.163	0.0497	0.0937*	-0.0563	0.0649	0.0309
	(0.0440)	(0.0527)	(0.0729)	(0.0481)	(0.126)	(0.0374)	(0.0567)	(0.0556)	(0.0424)	(0.0994)
H30MNE	-0.0279	-0.0321	-0.00795	-0.0515**	0.00363	0.0133	0.0177	0.0218	-0.000214	0.0238
	(0.0213)	(0.0260)	(0.0406)	(0.0260)	(0.0412)	(0.0236)	(0.0280)	(0.0366)	(0.0309)	(0.0383)
R30MNE	-0.229	-0.324	-0.873	-0.0506	-0.463	0.168	0.417	-1.039**	-0.0191	0.526
	(0.301)	(0.333)	(0.728)	(0.367)	(0.588)	(0.294)	(0.378)	(0.526)	(0.369)	(0.518)
B30MNE	-0.0234	0.0216	-0.0548	-0.00952	0.00372	0.0962**	0.0919	0.0678	0.107**	-0.00171
	(0.0414)	(0.0487)	(0.0884)	(0.0444)	(0.150)	(0.0473)	(0.0586)	(0.0760)	(0.0515)	(0.109)
F30MNE	-0.00972	0.0127	-0.0828	-0.0574	0.191	0.0500	0.0144	0.0837	-0.00738	0.217*
	(0.0523)	(0.0704)	(0.0835)	(0.0539)	(0.138)	(0.0470)	(0.0583)	(0.0705)	(0.0483)	(0.130)
H60MNE	-0.0115	0.0156	-0.0243	0.0187	-0.0840**	-0.0165	0.00331	-0.0105	0.0239	-0.0940**
	(0.0215)	(0.0254)	(0.0385)	(0.0245)	(0.0399)	(0.0214)	(0.0261)	(0.0340)	(0.0247)	(0.0414)
R60MNE	0.693***	0.712***	1.284***	0.792***	1.056**	-0.0548	-0.315	0.890*	0.176	0.000593
	(0.216)	(0.238)	(0.484)	(0.256)	(0.497)	(0.260)	(0.306)	(0.487)	(0.309)	(0.512)
B60MNE	0.0787**	0.0661	0.0736	0.0752*	0.147	-0.0119	-0.0301	0.0485	-0.0123	-0.0206
	(0.0348)	(0.0419)	(0.0651)	(0.0402)	(0.102)	(0.0350)	(0.0410)	(0.0639)	(0.0387)	(0.0953)
F60MNE	-0.0297	-0.0289	-0.0942	-0.00625	-0.108	-0.0310	0.0159	-0.0836	-0.0142	-0.0664
	(0.0399)	(0.0500)	(0.0853)	(0.0432)	(0.110)	(0.0411)	(0.0500)	(0.0618)	(0.0448)	(0.117)
H90MNE	0.00989	0.0199	-0.0605*	0.00902	0.00756	0.0138	0.00897	-0.0142	0.00572	0.0289
	(0.0163)	(0.0188)	(0.0358)	(0.0193)	(0.0363)	(0.0161)	(0.0192)	(0.0322)	(0.0196)	(0.0329)
R90MNE	0.114	-0.223	0.988**	0.151	-0.492	0.315	0.118	0.498	0.294	-0.139
	(0.254)	(0.289)	(0.496)	(0.302)	(0.493)	(0.271)	(0.307)	(0.438)	(0.348)	(0.478)
B90MNE	0.0273	0.0322	-0.0683	0.0408	-0.0886	0.0184	0.0405	0.0235	0.0477	-0.0453
	(0.0244)	(0.0291)	(0.0548)	(0.0263)	(0.0761)	(0.0281)	(0.0353)	(0.0483)	(0.0316)	(0.0786)
F90MNE	-0.0333	-0.0385	-0.0544	-0.0189	0.0135	0.0166	0.0229	0.0108	0.0514	-0.203**
	(0.0329)	(0.0408)	(0.0529)	(0.0350)	(0.0959)	(0.0316)	(0.0434)	(0.0452)	(0.0348)	(0.0851)
Export (log)	0.00241**	0.00180	0.000498	0.00267**	0.00246	0.00261**	0.00187	0.00168	0.00371***	-0.000874
	(0.00102)	(0.00155)	(0.00142)	(0.00117)	(0.00214)	(0.00111)	(0.00166)	(0.00138)	(0.00129)	(0.00239)
HI 2 digit	-0.0126	-0.00589	-0.0225	0.00129	-0.00199	0.0125	-0.00132	0.0657	0.00933	0.0704
	(0.0219)	(0.0264)	(0.0498)	(0.0266)	(0.0456)	(0.0228)	(0.0288)	(0.0449)	(0.0311)	(0.0433)
Bckw Output (log)	0.000182	6.65e-05	0.00350	-0.000204	0.00113	-0.00306*	-0.00219	-0.00501	-0.00271	-0.00400
	(0.00161)	(0.00193)	(0.00348)	(0.00188)	(0.00335)	(0.00186)	(0.00237)	(0.00317)	(0.00213)	(0.00406)
Observations	80,382	58,833	18,680	58,846	20,656	129,001	93,351	32,601	91,749	36,119
R-squared	0.902	0.897	0.924	0.907	0.900	0.831	0.838	0.850	0.823	0.851
City Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISIC5 Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

MNE spillovers through backward linkages and relatedness are consistently found between 30 and 60 km, throughout our specifications. The only exception is in Column 5, when we focus on non-exiting firms in high-tech industries. For what concerns the geography of Indonesia, we divide our sample between the two main islands of the country: Sumatra and Java (and Bali). The former is the largest island of the archipelago (approximately two times the size of the UK) and hosts about one fifth (50 million) of the Indonesian population. Java island, while considerably smaller (about half of the size of the UK), is highly densely populated (about 145 million people, out of the roughly 270 million Indonesians). The differences in density between the two islands are clearly reflected in the number of observations in our sample. The results in Columns 6, 7 and 8 of Table 8 suggest that relatedness spillovers are prevalent in Java and Bali but absent in Sumatra. Interestingly, in the latter, MNE spillovers are still present but confined to within municipality and to backward linkages. These results are interesting because they potentially suggest different spatial reaches of MNE spillovers depending on the intensity of agglomeration effects and network linkages (Breschi and Lissoni, 2009; Bathelt et al., 2004).

6 Conclusion

Over recent decades, numerous contributions have helped us understand and clarify how MNEs affect the hosting economy (Barba Navaretti and Venables, 2006). An important field of research has emerged and matured investigating MNEs as sources of spillovers to domestic firms, particularly through value chain relations (Meyer and Sinani, 2009; Javorcik, 2015; Rojec and Knell, 2018). In this paper, we attempt to contribute to and expand this field of research by examining three main issues: i) industrial relatedness as an alternative channel for spillovers at the firm level (Hidalgo et al., 2007; Cortinovis et al., 2020); ii) spatial distance affecting MNE externalities (Halpern and Muraközy, 2007; Resmini, 2019); and iii) the heterogeneous effects in relation to domestic firm characteristics. Whereas few firm-level analyses on relatedness-mediated spillovers already exist (Lo Turco and Maggioni,

Table 8: Robustness checks

VARIABLES	(1) TFPWME - NoEx	(2) TFPWME - NoEx SM	(3) TFPWME - NoEx L	(4) TFPWME - NoEx Low	(5) TFPWME - NoEx High	(6) TFPWME - Sumatra	(7) TFPWME - Java & Bali	(8) TFPWME - Main islands
HMNE	-0.0402	-0.0299	-0.111**	-0.0489	-0.0133	0.0439	-0.0613**	-0.0473*
	(0.0281)	(0.0323)	(0.0508)	(0.0319)	(0.0675)	(0.0741)	(0.0287)	(0.0275)
RMNE	0.283	0.157	-0.518	0.266	0.549	-0.921	0.138	0.150
	(0.321)	(0.370)	(0.608)	(0.358)	(0.794)	(1.009)	(0.338)	(0.310)
BMNE	0.0166	0.0133	0.0647	0.0126	-0.171	0.367**	0.0166	0.0209
	(0.0377)	(0.0506)	(0.0732)	(0.0381)	(0.145)	(0.174)	(0.0380)	(0.0369)
FMNE	-0.0205	0.00578	-0.177**	-0.0415	0.271	-0.0220	-0.00320	-0.00466
	(0.0430)	(0.0521)	(0.0723)	(0.0444)	(0.189)	(0.131)	(0.0453)	(0.0436)
H30MNE	-0.0308	-0.0341	-0.0262	-0.0435*	-0.0442	0.127	-0.0401*	-0.0269
	(0.0215)	(0.0265)	(0.0408)	(0.0239)	(0.0483)	(0.0816)	(0.0221)	(0.0209)
R30MNE	-0.233	-0.320	-0.585	0.0297	-1.773*	1.029	-0.193	-0.198
	(0.310)	(0.337)	(0.726)	(0.336)	(0.917)	(1.166)	(0.313)	(0.300)
B30MNE	-0.0395	0.00574	-0.0531	-0.0323	-0.00765	0.110	-0.0101	-0.0101
	(0.0441)	(0.0557)	(0.0919)	(0.0448)	(0.173)	(0.296)	(0.0408)	(0.0406)
F30MNE	-0.00294	0.0346	-0.0735	-0.0382	0.224	0.0926	-0.0243	-0.00415
	(0.0509)	(0.0707)	(0.0911)	(0.0507)	(0.209)	(0.157)	(0.0533)	(0.0524)
H60MNE	-0.0260	0.00453	-0.0710*	-0.00130	-0.0678	-0.111	-0.000220	-0.00270
	(0.0219)	(0.0265)	(0.0393)	(0.0231)	(0.0582)	(0.0809)	(0.0209)	(0.0204)
R60MNE	0.753***	0.832***	1.052**	0.771***	1.829***	1.095	0.627***	0.685***
	(0.230)	(0.260)	(0.498)	(0.265)	(0.679)	(1.081)	(0.225)	(0.214)
B60MNE	0.0990***	0.0699*	0.129*	0.105***	-0.0136	0.386	0.0670*	0.0660*
	(0.0356)	(0.0415)	(0.0681)	(0.0382)	(0.135)	(0.353)	(0.0344)	(0.0343)
F60MNE	-0.0133	-0.0278	-0.109	-0.0223	0.173	-0.0862	-0.0234	-0.0212
	(0.0400)	(0.0517)	(0.0877)	(0.0411)	(0.166)	(0.182)	(0.0393)	(0.0384)
H90MNE	0.00109	0.0107	-0.0778**	0.00779	-0.0223	0.138	0.00769	0.00837
	(0.0175)	(0.0200)	(0.0367)	(0.0191)	(0.0484)	(0.0967)	(0.0167)	(0.0161)
R90MNE	0.0434	-0.440	1.122**	0.183	-1.597**	2.166	-0.0613	0.0367
	(0.258)	(0.311)	(0.497)	(0.274)	(0.777)	(1.323)	(0.262)	(0.250)
B90MNE	0.0324	0.0274	-0.0814	0.0308	-0.0528	-0.174	0.0328	0.0330
	(0.0273)	(0.0345)	(0.0573)	(0.0287)	(0.0999)	(0.384)	(0.0243)	(0.0238)
F90MNE	-0.0362	-0.0244	-0.0524	-0.0248	0.0238	-0.0610	-0.0313	-0.0321
	(0.0308)	(0.0384)	(0.0555)	(0.0312)	(0.131)	(0.183)	(0.0344)	(0.0335)
Export (log)	0.00271**	0.00195	0.000914	0.00302***	-0.00162	0.00855***	0.00196*	0.00293***
	(0.00107)	(0.00156)	(0.00156)	(0.00113)	(0.00340)	(0.00215)	(0.00112)	(0.000981)
HI 2 digit	-0.00479	-0.00163	-0.0128	-0.00174	0.0145	-0.0562	-0.00993	-0.0162
	(0.0229)	(0.0282)	(0.0476)	(0.0253)	(0.0669)	(0.0780)	(0.0239)	(0.0225)
Bckw Output (log)	-0.000849	-0.00119	0.00400	-0.000748	0.00667	-0.00676	0.00144	0.000761
	(0.00177)	(0.00225)	(0.00348)	(0.00190)	(0.00511)	(0.00518)	(0.00175)	(0.00162)
Observations	66,834	47,936	16,416	59,662	6,485	7,034	68,492	76,028
R-squared	0.902	0.901	0.922	0.906	0.859	0.916	0.907	0.906
City Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISIC5 Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2019; Csáfordi et al., 2020; Howell, 2020), the spatial reach of MNE spillovers from input-output relations and through relatedness have been largely neglected. Given the importance of multinationals as engines for local development and structural change (Crescenzi and Iammarino, 2017; Crescenzi et al., 2020), and the increasing reliance on FDI attraction agencies (Harding and Javorcik, 2011; Crescenzi et al., 2019), a more fine-grained spatial perspective can foster an improved understanding of MNE spillovers and their micro-level dynamics.

In our theoretical framework, we have put forward four hypotheses. The first of them considered, in general, the role of relatedness as a channel for MNE spillovers. Although less spatially encompassing than expected, relatedness-mediated spillovers appear to be both greater in size and in significance than those channelled through backward linkages. This result offers a confirmation of Hypothesis 1 and suggests a possibly important role for this type of spillover to be explored by future research. Hypothesis 2 instead focused on the spatial extent of MNE spillovers. Our findings suggest that MNE spillovers through backward linkages and relatedness are not significant within the same municipality but exert productivity-enhancing effects at short (31 to 60 km) and medium (only for backward linkages, between 91 and 120 km) distances before turning insignificant again for further distance bands. Although we do not find a continuous decaying pattern, our results are strongly robust to a number of changes both in the model specification and in the sample. This may suggest that our findings are likely to be affected by the heterogeneous distribution of domestic and foreign firms in Indonesia and the specific spatial distribution in Indonesian cities. Hypotheses 3 and 4 also offer interesting insights. Specifically, smaller firms appear to be constrained in their spatial reach as opposed to larger firms because the latter benefit from productivity-enhancing relatedness spillovers at up to 90 km. Finally, firms in less-advanced industries benefit from relatedness-mediated effects as much as those in more-advanced sectors. Besides, for less-sophisticated firms, backward linkages are particularly important because they positively influence productivity at up to 90 km.

A number of relevant policy implications can be derived from our results. Crescenzi and Iammarino (2017); Crescenzi et al. (2019) indicate that MNEs can contribute to regional development if appropriately leveraged by policy-makers. Our results further confirm the possible role of MNEs as sources of spillovers, especially at short and medium distances. At the same time, we also indicate that significant heterogeneity exists with respect to how these effects materialise. For instance, larger firms even when located at a relatively higher distance (up to 90 km) are able to benefit from spillovers from MNEs in related industries. At the same time, certain channels may be particularly suitable for firms in certain industries. Low and medium-low tech sectors, for example, are shown to experience an increase in productivity when exposed to MNE spillovers through backward linkages at up to 90 km. It is, therefore, important that policy-makers consider such possible sources of heterogeneity when designing measures to attract MNEs.

We wish to draw attention to some potential limitations of our analysis. A first limitation is that we cannot model distance in a continuous way because our data do not provide information on the exact location of firms. Although our approach leverages highly fine-grained data on municipalities and represents an improvement on previous contributions in the literature, modelling spatial relations in a more detailed manner may offer interesting insights. A second limitation pertains to the insufficient information to proxy for absorptive capacity. Whereas previous versions of the Indonesian manufacturing survey appear to have a consistent reporting on human capital, this is not the case for our database (information on employees with a high-school diploma has about 60% of missing values). Because size is a suboptimal proxy for absorptive capacity (Zou et al., 2018), our results on this form of capacity would benefit from further testing with more reliable data. Lastly, whereas our model specification is highly demanding and includes a number of fixed effects (city-year and sector-year), we cannot fully exclude possible endogeneity issues.

Finally, some interesting areas for further research have emerged in relation to our findings. First, relatedness appears to be an important channel for spillover effects, but it should be subject to more research. Possibly interesting results may also emerge by comparing different types of relatedness, for instance based on patenting or labour mobility in addition to industrial proximity. Second, as in most studies in the literature, our vertical spillover measures are derived from national level input-output tables. However, as transaction-level data become available (Alfaro-Urena et al., 2019), it would be interesting to explore the geographical scope of transactions between foreign and domestic firms.

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