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Multinational enterprises, industrial relatedness and employment in European regions

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MULTINATIONAL ENTERPRISES, INDUSTRIAL RELATEDNESS AND EMPLOYMENT IN EUROPEAN REGIONS[1]

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Abstract

This paper looks at the link between Multinational Enterprises (MNEs) and employment in local firms in their host regions. The paper cross-fertilizes the literature on MNE spillovers with the emerging body of research on industrial relatedness. This paper empirically tests the link between industrial relatedness and MNE impacts on employment by capturing various types of horizontal and vertical similarities across industries. The focus of our study is on employment in European NUTS2 regions. The empirical analysis shows that cross-sectoral MNE spillovers among cognitively related industries are positive and significant, confirming that industrial relatedness is an important driver of employment-enhancing spillovers from MNE activities. However, positive effects of MNEs on domestic employment are contingent upon the modeling of both regional and industrial heterogeneity.

Keywords: Foreign Direct Investment (FDI), Relatedness, Employment, Europe, Regions.

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INTRODUCTION

The capability of firms to control and organize their activities in multiple countries and the corresponding increase in global investment flows have fostered scholarly and policy debates on multinational enterprises (MNEs), their ability to take advantage of specific locations and their effects on the host economies (Narula and Dunning, 2000; Fu et al., 2011; Javorcik, 2013). The existing literature in economics, economic geography and international business has highlighted a number of mechanisms through which MNEs may have a positive impact on domestic firms, for example in terms of innovation and productivity, especially when pursuing knowledge intensive and innovative activities in the host economy (Javorcik et al., 2017). In light of this evidence countries and regions across the globe actively compete with each other in order to attract foreign investors (Narula & Pineli, 2016; Bitzer et al., 2008; Harding & Javorcik, 2011). However, more recently, new empirical research has highlighted various potential ambiguities in the link between MNE activities and local innovation, development and wealth, shedding new light on the pre-conditions that need to be in place for these positive effects to materialize (Crespo and Fontoura, 2007; Görg and Greenaway, 2004).

The inflow of foreign direct investment (FDI) may stimulate product upgrading in the host country. Multinationals are often seen as key generators of innovation, accounting for a large share of global R&D spending as well as possessing superior knowledge on the suitability of the host country for the production of a specific products (Javorcik et al., 2017). Empirical evidence indeed confirms that multinationals transfer knowledge to their foreign affiliates (Arnold and Javorcik 2009) and that foreign affiliates are more likely to introduce new products than their indigenous competitors (Brambilla, 2009; Guadalupe et al., 2012). Yet, spillover effects to firms in host economies may be negative. MNEs may actively protect their knowledge in order to minimise knowledge leakages in favour of domestic competitors. Competition from MNEs may actually lead to negative productivity and innovation effects on domestic firms (Aitken & Harrison 1999). These mechanisms typically refer to horizontal spillovers from foreign to domestic firms operating in the same industry. Apart from MNEs potentially operating in different markets than domestic firms (e.g. top segments versus local market segments), these considerations led most researchers to a conclusion that the existence of horizontal spillovers is very limited (Havranek et al., 2011; Lin et al., 2007; Javorcik 2004; Javorcik et al., 2017). In contrast, vertical (i.e. inter-industry) spillovers are far more likely, since multinationals may have incentives to provide technology to their suppliers (backward spillovers), and probably also to their customers (forward spillovers) (Lu et al., 2017).

The aim of this paper is to contribute to the debate on MNE externalities and domestic firm performance by cross-fertilizing the MNE spillovers literature with the growing literature on industrial relatedness (Hidalgo et al., 2007). This paper empirically tests the link between relatedness and the impact of MNEs on employment in domestic firms. By adopting a relatedness perspective the paper can capture various types of horizontal and vertical similarities across industries complementary to (vertical) input-output linkages. The focus of our study is on the effect of MNEs on employment in European regions. Given that knowledge intensive industries and product relatedness are generally associated with employment opportunities, we look at sectoral employment in European (NUTS2) regions to test hypotheses on their relation with MNEs in the same and related sectors, their interactions with local absorptive capacities and institutional and development stages. In light of the considerable regional differences in terms of knowledge, sectoral composition and overall level of development, we address the heterogeneity of MNE effects by capturing sectoral and regional specific conditions and mechanisms of spillovers. Although we control for sector-region and year fixed effects, it is possible that some unobservable factors varying at the sector-region-year level could be affecting our findings or that MNEs may anticipate local firms' ability to learn and employ people and therefore MNEs locate in those areas. To address these possibilities, we rely on a Bartik-type instrument (Crescenzi et al., 2015; Ascani and Gagliardi, 2015) to approximate the distribution of MNEs across regions and sectors while purging region-industry specific characteristics and test the robustness of our results.

Our empirical analysis shows that cross-sectoral MNE spillovers among cognitively related industries are positive and significant. This provides an initial confirmation to the idea that industrial relatedness - possibly encompassing but not limited to I-O relations – is an important driver of employment-enhancing spillovers from MNE activities. While the use of relatively aggregated sectors does not allow us to capture relatedness at a fine-grained level, the influence of MNEs on cognitively related industries across two-digit NACE sectors, confirms the importance of looking beyond vertical linkages. These results however are contingent on the modeling of both regional and industrial heterogeneity. The explicit consideration given to regional and industrial heterogeneity represents a second contribution of this paper. In line with previous studies (Fu et al., 2011; Bitzer et al., 2008), we find that intra-industry effects are not negligible, and tend to be stronger in relatively less economically advanced regions rather than more developed areas.

The paper is organized as follows. In the first section, the relevant literature on MNE externalities, their preconditions and their intra- and inter-industrial scope is reviewed, underlining the limitations of a focus on vertical inter-industry spillovers only, and the potential contributions from including cognitive industrial relatedness. Based on these considerations, we developed four testable hypotheses in the second section of our paper. Following, the modeling choices, the methodology applied, the identification strategy and the data to test these hypotheses are presented, before moving to the discussion of our econometric results. In the last section, we summarize the contributions of our work, also stressing its limitations and highlighting some directions for further research and policy implications.

LITERATURE REVIEW

Multinational enterprises (MNEs) are among the most important actors in the process of knowledge creation and diffusion. Thanks to their technological capabilities and their capacity to control activities in multiple technological environments, MNEs can leverage their network of subsidiaries and exploit local knowledge resources in different places (Narula and Dunning, 2000; Ernst and Kim, 2002; McCann and Iammarino, 2013). On this basis, foreign subsidiaries bring about externalities for domestic firms, some of which may lead to higher employment and productivity (Javorcik, 2013; Crescenzi et al., 2015).

MNE spillovers

In the last decades, a significant amount of research has studied the impact of MNE subsidiaries on the host economy (Perri and Peruffo, 2016; Burger et al, 2013; Karreman et al, 2017). The literature in this field has contributed to unveil the set of mechanisms, dynamics and preconditions linking the presence of international companies with potential beneficial effects for the local economy.

The presence of multinational companies can affect, either positively or negatively, the host economy. Theoretical and empirical contributions have established the different channels through which these externalities occur. Firstly, local companies can learn and imitate the technologies and procedures used by MNEs (Crespo and Fontoura, 2007; Ernst and Kim, 2002). In the same way, the MNE network abroad can give insights about foreign tastes and relational channels, facilitating the internationalization of domestic firms (Görg and Greenaway, 2004). Secondly, the increase in competition due to the entry of an MNE can force domestic companies to become more efficient and make better use of existing technologies and resources. However, competitive pressure might also be harmful: more advanced MNEs may push competitors out of the market or induce local companies to operate on a smaller and less efficient scale (Fu et al., 2011). Thirdly, domestic firms can acquire specialized knowledge by hiring workers previously employed in an MNE. Labor mobility however can also work in the opposite direction. MNEs tend to offer higher wages than domestic ones, making them more attractive for the most talented workers in the market (Javorcik, 2013).

Preconditions for MNE spillovers

Different contributions in the literature have highlighted how local conditions and MNE characteristics may affect the ability of domestic firms to benefit from the presence of foreign companies (Ernst and Kim, 2002; Perri and Peruffo, 2016). Productivity and knowledge spillovers are found to be more marked in economies with higher levels of development (Crespo and Fontoura, 2007; Meyer and Sinani, 2009), whereas the picture is more mixed for transition and developing economies (Görg and Greenaway, 2004; Bitzer et al., 2008; Javorcik, 2013). This relation between local development and MNE spillovers depends however on more fundamental factors, affecting the ability of domestic firms to benefit from MNE presence (Fu et al., 2011). The literature on FDI distinguishes respectively (vertical and horizontal) market-driven, (horizontal) efficiency-driven, (vertical) resource-driven, and (horizontal, cognitive) knowledge-driven investments (Barba Navaretti and Venables, 2004; Burger et al., 2013). One of the most relevant elements in the latter category is the technological gap between local firms and multinationals. Whereas larger difference in terms of technological endowment between domestic and foreign firms entails greater room for learning, a larger gap is also more difficult to close (Kokko, 1994; Boschma, 2005). The relation between spillovers and technological gaps has an inverse-U shape: from the one hand, no transfer can take place if there is no difference in technology and knowledge; from the other hand, if the gap is too wide, local firms will not be able to learn from the foreign counterpart (Fu et al., 2011).

A second critical factor is the local "absorptive capacity" (Narula and Dunning, 2000; Blomström and Kokko, 2003), conceptually linked to the levels of R&D and human capital both at firm and local level (Cohen and Levinthal, 1990). The fact that firms and regions with larger absorptive capacity are in better position to benefit from MNE spillovers bear some implications as for what type of industries have more chances to profit from MNEs. Given the greater availability of knowledge resources in advanced industries, both theory and empirics indicate that MNE have stronger impacts in more knowledge-intensive sectors (Crespo and Fontoura, 2007; Fu et al., 2011).

Various other factors may determine the spillover effects of foreign firms on domestic ones. Institutional features, such as trade policy, tax incentives, community presence, intellectual property rights and the solidity of the financial system influence the location choices of MNEs, and thus of their spillovers (Blomström and Kokko, 2003; Alfaro et al., 2004; Cipollina et al., 2012, Karreman et al., 2017). Similarly, the origin (Narula and Dunning, 2000; Crespo and Fontoura, 2007), the mode of entry (via greenfield or M&A) and the reason for entry (efficiency-seeking or market-seeking) of foreign companies have been associated to a larger or lesser ability to generate spillovers (Neto et al., 2008; Beugelsdijk et al., 2008). Finally, the effects of MNEs may reduce in sectors already hosting a significant number of foreign firms (Altomonte and Pennings, 2009).

Intra-industry and inter-industry spillovers

One of the most important characteristics of MNEs is the knowledge and human capital resources they control (McCann and Iammarino, 2013). The protection of their intangible assets and the mitigation of risks of knowledge dissipation represent theoretical answers to the ambiguous empirical results on intra-industry spillovers. If the survival of a foreign subsidiary strongly depends on its knowledge assets and its ability to internalize the benefits deriving from those, the prevention of knowledge spilling to local competitors is of paramount importance (Görg and Greenaway, 2004; Javorcik, 2004). The strong incentive to minimize knowledge spillovers would thus curb the positive externalities deriving from the MNE presence. Unlike, in inter-sectoral relations MNEs may face different incentives. To ensure efficient and positive cooperation with local firms when needed, foreign companies may be more prone to share part of their knowledge. The presence of MNEs in a given industry may thus have implications also outside the sector to which they belong (Ernst and Kim, 2002; Kugler, 2006).

In the quest for cross-sectoral MNE spillovers, most of the literature has identified input-output relations as the main channel through which such externalities may occur (Perri and Peruffo, 2016; Lu et al.,2017; Lin et al., 2007). Vertical linkages to MNEs engender productivity-enhancing spillovers for instance through increased demand for local goods or larger competition for supplying multinationals (Javorcik, 2004; 2013; Crespo et al., 2009). Besides, to guarantee certain quality or technical standards, foreign companies have the incentive to share valuable knowledge to local producers (Ernst and Kim, 2002), through visit and periodic inspections (Javorcik, 2004) or training programs (Fu et al., 2011). Similar dynamics apply to forward linkages too. By sourcing from MNEs, local firms may benefit from goods of greater quality or more technologically advanced, which in turn may streamline their production process, fostering efficiency and productivity (Crespo and al, 2007; Javorcik, 2004). Specific knowledge might also be acquired along with the good itself (Coe and Helpman, 1995) or via after-sale care or support services.

Whereas studies on within-industry spillovers often give inconclusive results (Fu et al., 2011), significant evidence exists confirming the relevance of inter-industry effects

(Kugler, 2006; Crespo et al., 2009; Javorcik, 2013). In general, these analyses suggest that backward linkages positively contribute to the increase in level of productivity within the local economy (Javorcik, 2004; Bitzer et al., 2008; Crespo et al., 2009; Lin et al., 2007), with few exceptions (Damijan et al., 2003). Unlike, forward linkages do not seem to have significant effect on local productivity, in some cases even having a negative impact on domestic firms (Crespo and Fontoura, 2007).

Within the debate on inter- and intra-sectoral MNE spillovers, types of linkages different from input-output relations have received minor if any attention. This contrasts with other literatures, which consider a broader set of dimensions through which knowledge can flow across industries. In economic geography and agglomeration literature, externalities are hypothesized and empirically found to occur especially from the recombination of both proximate (Boschma, 2005; Frenken et al., 2007) and highly diverse types of knowledge (Jacobs, 1969; Glaeser et al., 1992). The concept of relatedness aims at capturing how knowledge, technologies and assets already present in a (local) economy influence the possibility to diversify over time (Hidalgo et al., 2007). In other words, the opportunities for an economy to diversify and operate in a new (for the region) sector depend on the industries already present in the economy: the more two sectors are cognitively related, the easier it is for firms to re-deploy their assets, acquire new capabilities, and move from one sector to the other (Hidalgo et al., 2007; Hausmann and Klinger, 2007; Cortinovis et al., 2017; Boschma and Capone, 2015; Boschma et al., 2013). The concept of relatedness synthesizes the different dimensions in which two sectors can be proximate, be it because of similar technologies, skills or production processes, because of input-output relations, or because of similar institutional arrangements (Hidalgo et al., 2007).

Foreign-owned companies, with their ability to gather and use knowledge and technologies from different locations (Narula and Dunning, 2000; McCann and Iammarino, 2013; Crescenzi et al., 2015), may bring about significant cross-industrial knowledge flows outside of their own value chains. For instance, management practices or organization of the production – such as the “lean production” systems – represent a set of general capabilities, initially applied in automotive, but now diffused in manufacturing of a variety of goods, as well as in retail and distribution (McCann and Iammarino, 2013). While more specialized knowledge is more difficult to be redeployed, this can still happen. Technical expertise may provide valuable knowledge and abilities to successfully operate in similar industries, as in the case of spin-off dynamics (Boschma and Frenken, 2011). Boschma and Wenting (2007), for instance, show how the chances of survival for entrepreneurs in car manufacturing in Britain were higher if they had previous experience in technically similar but vertically unrelated industries, such as bicycle production or industries using mechanical engineering skills. On this basis, confining the impacts of MNEs within the boundaries of backward and forward linkages might offer at best a partial picture of the cross-sectoral spillovers.

Contributions in industrial relatedness and variety externalities can complement the literature on inter-industry spillovers of MNEs. The international business literature has so far mostly argued that cross-sectoral effects of MNEs are mediated by vertical linkages. Unlike, the literature focusing on different types of proximity (Boschma, 2005, Nooteboom 2000) has convincingly argued that interactive learning occurs more easily when two parties exhibit some degree of cognitive or technological relatedness. This implies that firms may learn from each other even when operating in sectors separated in terms of input-output relations, but similar in terms of knowledge, skills and technologies. Besides, the international business literature uses arguments similar to those of Boschma (2005) in relation to the technological gap between domestic and foreign firms (Kokko, 1994; Fu et al., 2011); however, their implications in terms of cross-sectoral (horizontal and vertical) knowledge spillovers have not been fully addressed.

Following the relatedness literature we propose that knowledge in one sector can find useful applications also in different but cognitive related sectors. Whereas this idea of cognitive relatedness may encompass also vertical linkages (Hidalgo et al., 2007), it specifically entails the possibility of knowledge spilling over horizontally to proximate sectors. The channels for knowledge spillovers already identified in the literature, such as labor mobility, demonstration effects or other informal linkages (Ernst and Kim, 2002; Perri and Peruffo, 2016), can thus be expected to work not only within vertical relations, but also connecting different but technologically or cognitively similar industries horizontally.

RESEARCH SETTING

The literature on the multinational corporations and their effects on the local economy has witnessed an upsurge in the last years. Such intensive attention contributed to the establishing of some stylized facts on MNEs, in particular with respect to their ability to diffuse knowledge, to generate positive externalities for domestic firms, and on the local preconditions for these beneficial effects to materialize (Ernst and Kim, 2002; Crespo and Fontoura, 2007). Nonetheless, our review of the literature in the introduction and the previous section problematized several important issues.

First, theoretical and empirical research suggest the existence of *both* intra- and inter-sectoral spillovers. The former derive from the presence of MNEs in the same sector in which domestic firms operate. The weak empirical support that has been found for this type of effects has been linked to need of foreign companies to limit positive externalities to competitors or the existence of competition-related externalities counterbalancing the knowledge spillovers. As the majority of research has looked at input-output relations for measuring channels for knowledge spillovers, the broader industrial linkages are undervalued: MNE spillovers may also flow to industries that are not connected via vertical linkages but related in terms of products, technologies and knowledge assets. Because such cognitive relatedness co-evolves with sectoral diversity more naturally than with specialization, more significant effects are expected for employment levels and dynamics than for productivity. No previous research considered the role of cognitive relatedness in MNE spillovers.

Second, the effects of MNEs on domestic firms are clearly mediated and influenced by local characteristics (Ernst and Kim, 2002; Görg and Greenaway, 2004; Meyer and Sinani, 2009). In areas that are lacking of essential assets, in terms of human capital, knowledge or institutional conditions, the impact of MNE is likely to be smaller. The same is true for regions in which the technological divide between domestic and foreign firms is minimal, so that domestic firms have little to learn from foreign ones. When local endowments of knowledge, technology and institutions are significant, the presence of foreign companies can have positive and economically meaningful effects (Fu et al., 2011). The focus of the present study is on the effect of MNEs in European regions. Given the considerable differences in terms of knowledge, sectoral composition and overall level of development in our sample (Annoni et al., 2017), our work aims at disentangling the heterogeneity of effects of foreign companies on the domestic regional economy.

Based on these considerations, we develop four hypotheses on the effects of multinational corporations on industries in European regions. In our baseline models, we want to study the intra-industry impact of MNE presence on local sectoral employment. Whereas the previous literature has provided ambiguous results, theoretically we can expect sectors with higher presence of foreign companies to perform better due to knowledge spillovers and competitive pressure.

Hypothesis 1:

> *The level of employment in a sector in a region is positively related with the presence of MNEs in the same sector-region.*

As argued in the previous sections, the main focus of this paper is on the study of industrial cognitive relatedness, and its ability to mediate MNE spillovers across sectors. Combining the literature on inter-industry MNE spillovers, diversity externalities (Jacob 1969; Glaeser et al., 1993; Frenken et al., 2007) and relatedness (Hidalgo, 2007; Boschma, 2005), we theorize that knowledge spillovers from foreign companies may have an impact on sectors related to that of the MNE. In hypotheses 2, we expect that presence of MNEs in cognitive related industries positively influences the focal industry, thanks to larger possibilities for knowledge spillovers, to lower competitive pressures, and to the lower risk of MNE enacting strategies for reducing externalities.

Hypothesis 2:

> *The level of employment in a sector in a region is positively related to the presence of MNEs in cognitive related industries in the same region.*

Our last two hypotheses deal with regional and industrial heterogeneity in our sample. Knowledge assets and absorptive capacity are necessary for benefitting from foreign companies (Görg and Greenaway, 2004; Crespo and Fontoura, 2007; Fu et al., 2011).

Against this background, we expect that relations to MNEs, both within the same industry and in related sectors, will have a stronger effect in more knowledge intensive industries, as they are better equipped in terms of human capital and R&D resources. In other words, as firms in knowledge intensive industries are more likely to better endowed with absorptive capabilities, the effects of spillovers from MNEs are likely to be stronger.

Hypothesis 3:

The positive effects of MNE presence, both within-industry and across-industry, are stronger for knowledge intensive industries in the target region.

Finally, the effects of MNEs have been shown to depend on the level of development of the target area, with firms in less developed regions benefitting less from foreign companies (Crespo and Fontoura, 2007; Javorcik, 2013). Whereas countries in our sample gather relatively developed economies, significant regional differences persist in the EU, with Southern (less growing) and Central Eastern European regions (less developed) being on average less prosperous than Western ones. At the same time, these areas are characterized by skilled workforce, relatively low wages and stable institutional systems, and are part of the EU Common market (Dogaru et al. 2015). In spite of its relatively lower level of development or growth, we argue that these factors make less-advanced EU regions in good positions to attract MNEs, absorb knowledge and stimulate growth and development (Protsenko, 2003; Bitzer et al., 2008; Damijan et al., 2003; Javorcik, 2004, 2013). On these bases, we hypothesize that:

Hypothesis 4:

The positive effects of MNE presence and entries, both within-industry and across-industry, are stronger in less advanced regions than in more advanced EU regions.

MODELS, METHODS AND DATA

Modeling framework

Investigating the relationship between MNEs and local economies poses a number of issues from an econometric point of view, for capturing the impact of related industries and with respect to endogeneity and reverse causality issues. The analysis proposed in this paper considers the short-term effects on total sectoral employment of MNE presence both within the same industry and in cognitively related ones.

In Model 1, the economic performance within each sector-region is modeled as a function of the number of MNE in the previous year. In formal terms:

$$y_{i,r,t} = \alpha_{i,r} + \tau_t + \delta MNE\_num_{i,r,t-1} + \lambda no\_MNE_{i,r,t-1} + \gamma Control_{i.r,t-1} + \varepsilon_{i,r,t}, \quad (1)$$

where $y_{i,r,t}$ stands for the level of employment[2] (in logs) in sector *i*, in region *r* at time *t*, $lnMNE$ represents the log count of MNE[3] at time t-1, while no_MNE is a dummy variable with value 1 when no foreign company is present in sector *i*, in region *r* at time *t-1*. Our model includes also control variables ($Control$) as well as sector-region ($\alpha_{i,r}$) and yearly (τ_t) fixed effects. Along with sector-region and yearly fixed effects, we control for within-region dependence in the error terms and potential heteroscedasticity by using robust and regionally clustered errors in all models.

Testing for hypothesis 2, requires a further extension of the baseline model discussed above, so to include the terms for capturing MNE presence in related industries. In the case of Model 2, the variable MNE_num is interacted with the proximity matrix **W** to generate MNE_num_rel (see Equation 2). This matrix, as explained in the next pages, captures the cognitive proximity between industries based on the co-occurrence of pair wise specializations.

$$y_{i,r,t} = \alpha_{i,r} + \tau_t + \delta MNE\_num_{i,r,t-1} + \rho\, MNE\_num\_rel_{i,r,t-1} + \lambda no\_MNE_{i,r,t-1} + \gamma Control_{i.r,t-1} + \varepsilon_{i,r,t}, \quad (2)$$

[2] The choice of using employment as measure of the performance of the industries instead of wages is motivated by the fact that salaries adjust to the levels of productivity differently in different countries. This, in turn, may make wage a less reliable proxy for productivity.

[3] As discussed more thoroughly in the section on data and in Appendix 2, our dataset captures the presence, entry and exit of foreign firms, both via M&A and foreign direct investments.

We test for hypotheses 3 and 4 by splitting the sample in regimes according to different types of sectors and regions (cf. Ertur and Koch. 2007). In other words, the same models will be estimated separately for advanced industries[4], knowledge-intensive services and low-knowledge sectors, as well as for more prosperous EU regions and for less developed EU regions.

Methodology

As underlined in the discussion of the literature, one of the main limitations in the study of MNE externalities has been the almost exclusive consideration given to vertical linkages as channels for inter-industry spillovers. In this paper we explore whether MNE effects are perceived across industries, industries using a cognitive proximity measure.

For doing so, we apply the concept of relatedness proposed by Hidalgo et al. (2007), following a method proposed by Van Eck and Waltman (2009) and refined by Steijn (2016). These methods allow to create a measure of similarity across different types of objects, in our case industries at the 2-digit of NACE classification. To perform these calculations, we used data on sectoral employment in 2006 from the Bureau Van Dijk Orbis database (cf. Variables and Data and Appendix 2). We choose to use only data from 2006 in order to reduce possible endogeneity.

Like in the work by Hidalgo et al. (2007), we start by defining the sectors in which each region is specialized. We consider region r to be specialized in sector i when it's location quotient for that sector is larger than one. In more formal terms:

$$LQ_{ir} = \left(\frac{E_{ir}/E_{*r}}{E_{i*}/E_{**}}\right), \tag{5}$$

and

[4] See Appendix 1 for details on the subdivision of sectors and regions in different categories.

$$x_{i,r} = \begin{cases} 1, if\ LQ_{ir} > 1 \\ 0, otherwise \end{cases} \qquad (6)$$

Once the sectoral measure of specialization is computed, we count in how many regions specializations in sectors *i* and *j* co-occur. We then consider *i* and *j* related if they tend to systematically co-locate. Our measure of relatedness is thus calculated as the ratio between the observed co-occurrences and a random benchmark. Equation 7 represents formally the computation performed:

$$\varphi_{ij} = \frac{c_{ij}}{\left[\left(\frac{S_i}{T}\right)*\left(\frac{S_j}{T-S_i}\right)+\left(\frac{S_j}{T}\right)*\left(\frac{S_i}{T-S_j}\right)\right]*\left(\frac{T}{2}\right)}, \qquad (7)$$

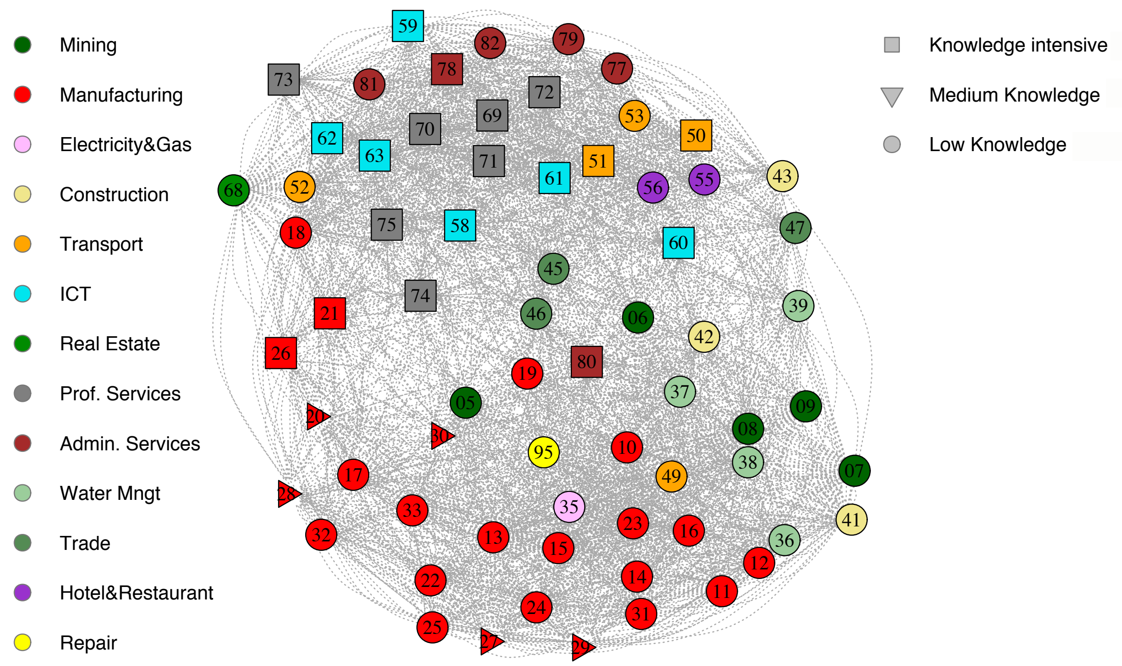
where c_{ij} is the co-occurrence count of specializations in sectors *i* and *j*, S_i and S_j are the total number of occurrence of *i* and *j* respectively, and T is the total number of occurrences of any sector. In the equation, the nominator is equal to the number of times (i.e. in how many regions) specializations in *i* and *j* occur together, while the denominator computes the number of co-occurrences under the assumption of the *i* and *j* are independent (Steijn, 2016).

The result of Equation 7 is a $n \times n$ **W** matrix, with *n* being the number of sectors in our sample. Each cell in **W** contains the cognitive relatedness score between two sectors, with each value ranging between 0 and infinity and taking value 1 when the expected number of co-occurrences is the same as expected under the random scenario. In order to capture the effects of strong relatedness across sectors, we exclude cells in the main diagonal of **W** and we set to 0 the cells with relatedness less or equal to 1. Finally, we rescale the values of the matrix to make them range between 0 and 1. As mentioned in the description of the models, we use the **W** matrix to capture the number of MNEs around sector *i*. We create the variable MNE_num_rel by simply multiplying the relatedness matrix **W** and the sectoral vectors of MNE_num in each region.

Figure 1 (below) gives a first-hand evaluation of the network of relatedness obtained and captured by **W**. Each node represents one of the 68 industries we collected data for, and the position relative to the other nodes is based on the pair wise relatedness scores

(Hidalgo et al., 2007). For sake of clarity, the graph depicts only linkages with values higher than average. As shown in the legend, round nodes are low-knowledge industries, whereas square nodes represent most advanced sectors, and each of the node is colored according the first-digit NACE sector it belongs to. As Figure 1 clearly highlights, sectors are not homogeneously related one to each other. Square nodes have sorted themselves in the left hand side of the graph, where the network relations appear to be denser. This indicates that knowledge intensive industries tend to be more closely related with each other and less with medium- and lower knowledge intensive sectors. Figure 1 thus gives some preliminary support to the idea that knowledge spillovers may be stronger within the knowledge intensive part of the economy (to be tested with Hypotheses 3) compared to spillovers across sectors with various degrees of knowledge intensity. A mirroring pattern emerges on the right part of the graph, where mostly low-knowledge intensive manufacturing industries locate. Also in this case the configuration suggests the existence of opportunities for cross-sectoral spillovers, although to a lesser extent and mostly from other low-knowledge industries.

Figure 1: Network representation of relatedness



Finally, it may be argued that the use of only 68 sectors for performing our analysis represents a limitation for this study. However, it should also be stressed that observing industries at such aggregate level allows us to reduce potential concerns for capturing spillover mediated by input-output relations, rather than horizontal knowledge flows. By analyzing relatively encompassing industries, we can more safely assume we mainly capture knowledge spillovers between horizontally related industries.

Variables and data

In order to construct our dataset, we resort to difference data sources, namely Eurostat, Cambridge Econometrics (CE) and Bureau Van Dijk (BVD). Table 1 reports the sources, period and descriptive statistics of the variables, while Table 2 shows the pairwise correlations. Larger details on the sectors and regions included in this study are in Appendix 1, and on the treatment of the data, especially from from BVD, in Appendix 2.

Table 1: Descriptive statistics

VARIABLES	N	Mean	sd	min	max
Empl (ln)	92,309	7.729	1.822	0	13.13
MNE_num (ln)	138,528	1.108	1.377	0	8.214
No_MNE (dummy)	138,528	0.337	0.473	0	1
MNE_num_rel (ln)	138,528	8.116	6.292	0	46.93
MNE exit (dummy)	138,528	0.0428	0.202	0	1
MNE entry (dummy)	138,528	0.301	0.459	0	1
MNE rel_exit (dummy)	138,528	0.0406	0.0888	0	0.922
MNE rel_entry (dummy)	138,528	0.288	0.302	0	1
TotR&D	137,520	1.526	1.229	0.0600	11.36
PhK (ln)	136,552	5.273	0.602	0.284	7.029
GDP (ln)	136,960	3.353	0.984	0.0751	6.242
HK_tert	136,960	0.122	0.0449	0.0366	0.328
Firm_num (ln)	98,014	5.466	2.003	-0.693	11.81
MNE_emp_sp (ln)	138,528	69.34	37.95	0	230.9
iv_b_nor_eu	138,528	12.98	49.33	0	2,436

As shown in Table 1, we resort to official data for computing our dependent variable, *emp_rate*. The Structural Business Survey (SBS) of Eurostat provides information at for 68 2-digit sectors on characteristics, among which the number of employees. Whereas most of the literature focuses on (total factor) productivity as dependent variable (Javorcik, 2004; Altomonte and Pennings, 2009; Beugelsdijk et al., 2008), we argued that employment is appropriate for analyzing innovative crossover opportunities

Table 2: Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Empl (ln)	**1**	1														
MNE_num (ln)	**2**	0.6	1													
MNE_num_rel (ln)	**3**	0.33	0.56	1												
No_MNE (dummy)	**4**	-0.5	-0.57	-0.38	1											
MNE exit (dummy)	**5**	0.34	0.43	0.25	-0.25	1										
MNE entry (dummy)	**6**	0.17	0.17	0.11	-0.12	-0.14	1									
MNE rel_exit (dummy)	**7**	0.29	0.24	0.39	-0.15	0.66	-0.08	1								
MNE rel_entry (dummy)	**8**	0.17	0.16	0.25	-0.11	-0.12	0.41	-0.19	1							
TotR&D	**9**	0.09	0.17	0.29	-0.13	0	0.03	0.02	0.06	1						
PhK (ln)	**10**	0.12	0.13	0.21	-0.14	0.02	0.04	0.04	0.09	0.46	1					
GDP (ln)	**11**	0.37	0.31	0.51	-0.27	0.12	0.09	0.19	0.19	0.41	0.44	1				
HK_tert	**12**	0.79	0.55	0.24	-0.39	0.33	0.14	0.23	0.09	0.02	0.04	0.24	1			
Firm_num (ln)	**13**	0	0.01	0.01	0.05	0.11	-0.01	0.14	-0.04	-0.19	-0.11	-0.17	0.1	1		
MNE_emp_sp (ln)	**14**	0.25	0.31	0	-0.18	0.08	0.08	-0.06	0.05	0.01	0.01	0	0.29	0.01	1	
iv_b_nor_eu	**15**	0.31	0.48	0.21	-0.17	0.19	0.08	0.08	0.05	0.09	0.05	0.19	0.35	0.02	0.29	1

between sectors in diversified economies that are prone to innovative spillovers from MNEs in the EU. The policy relevance of employment effects in a context of economic turmoil makes the use of employment rate as the dependent variable particularly interesting.

The main variables of interests in our paper are three. As a measure of the presence of MNE in a given sector, we use a count variable (in logs) for the number of foreign owned companies operating (*MNE_num (ln)* in Table 1). As explained above, *MNE_num_rel* reflects the interaction of *MNE_num* with the relatedness matrix **W**, and it captures the effects due to the presence of foreign companies in related industries. Finally, whereas no explicit hypothesis applies to *No_MNE*, the coefficient for this dummy variable can be considered of interest because it captures the average effect of hosting no foreign company in a given sector.

As mentioned in the presentation of Equations 1 and 2, our models include various control variables. *HK_tert* and *TotR&D* control for the knowledge endowment of each region (Crespo and Fontoura, 2007; Fu et al., 2011): the former is computed as the share of employees having obtained tertiary education over the working age population; the latter is the share of total R&D expenditure over regional GDP. Similarly, we included the level of GDP of the region (*GDP (ln)*) to control for the economic size of the region. Whereas these three variables are measured at regional level, *PhK* – measuring the share of capital formation over Gross Value Added (GVA) – is measured for the six "macro" sectors available from Cambridge Econometrics. Through *PhK* we are able to control for the level of investment in those macro-sectors (Basile et al., 2012). Finally, in order to control for local agglomeration economies and spatial effects, we included for each 2-digit NACE industry, the log number of local units sector (*Firm_num (ln)*) and the spatially lagged version of *MNE_num* (*MNE_num_sp (ln)*) (Alfaro and Chen, 2014). This last variable is computed by multiplying the log number of MNEs in each of the sectors of a neighboring region Z, for the measure of geographical proximity of Z and the focal region R.

ECONOMETRIC ANALYSIS

The results from our baseline models are reported in Table 3 and 4. In the tables, the heading of each column indicates whether the coefficients refer to the economy as a whole (All), to low-knowledge industries (LKI), to high-knowledge industries (HKI) or to knowledge intensive business services (KIBS). The heading also specifies whether the estimates refer to the whole sample, more advanced regions (with GDP per capita above the EU average in 2010) or less advanced areas (with GDP per capita below the EU average in 2010).

TABLE 3 AROUND HERE

The estimates reported in Table 3 confirm our Hypotheses 1, 3 and 4. More specifically, a high presence of foreign companies at time *t-1* is associated with a high level of employment at time *t* within the same sector. The coefficients for the variable *MNE_num* are in fact positive and significant across the different types of sectors. However, the size of the coefficients changes when the analysis is performed across different groups of industries: the effect of MNEs on local employment more than doubles when moving from less advanced industries (Table 3, column 2) to high-knowledge ones and knowledge intensive services (Column 3 and 4). As theorized in Hypothesis 3, more knowledge intensive parts of the economy are more strongly influenced by the presence of foreign companies. At the same time, however, sectors which host no foreign company do not seem to do significantly worse than the others. The coefficients for *No_MNE* are in fact negative, though only one of them is significantly different from zero. With respect to Hypothesis 4 and regional heterogeneity, the results of the baseline model suggest a stronger intra-industry effect of MNE in less advanced regions. Finally, whereas different control variables did not produce significant coefficients, the levels of investments (*PhK*) and of sectoral level agglomerations (*Firm_num*) are both strongly associated with higher employment rate, as expected.

The main focus of this analysis is on the use of cognitive relatedness for studying MNE inter-industry spillovers, investigated through our last two models. Table 4 reports the estimated coefficients for Equation 2.

TABLE 4 AROUND HERE

The estimates reported in the columns of Table 4 highlight heterogeneity in the relation between the presence of foreign companies and their employment effects on the hosting economy. Hypothesis 1 finds further support, as *MNE_num* remains positive and significant throughout most of the specifications. Also the differences in terms of the size of the coefficients between more and less advanced EU regions and between more and less knowledge intensive industries remain unchanged. Coefficients reported in Table 4 test also for Hypothesis 2, concerning the effect of MNE presence in related industries. The number of foreign companies from related industries appears to significantly impact sectoral employment, a part from most advanced regions. Remarkably, in line with the results for *MNE_num*, also *MNE_num_rel* indicates a stronger effect of MNE presence in related industries in the case of most knowledge intensive sectors. In line with Hypothesis 4, the effect of multinationals in related industries appears to be mostly driven by less-advanced regions: the coefficients for *MNE_num_rel* are always positive significant but in the case of regions with above-average per capita income.

To summarise, our main interest in this analysis was to study the employment effect of MNE presence within and across industries, as well as across different types of sectors and regions, using industry-pair co-occurrence relatedness rather than IO-relations as determining framework of identification. Our baseline hypotheses find overall support. Both the intra-industry impact (Hypothesis 1) and inter-industry effects (Hypothesis 2) of MNE appear to be positive, though with substantial differences across groups of industries and regions.

Instrumental variable estimation and robustness checks

Different methodological issues may be affecting the models and results discussed in the previous pages. A first concern reflects the fact that the location choice of MNEs is likely to be endogenous, thus implying that the relations found in the previous models may be due to reverse causality. Given the direct relation between location choices of the MNEs and sectoral performance, this problem is likely to be especially acute in the case of intra-industry effects. As multinationals select themselves in the region-industry pairs for location, it is unlikely they would choose to locate in areas performing comparatively worse than others or lacking critical resources such as suitable infrastructure, human capital or other intangible assets (see Karreman et al. 2017). This implies that the current number of MNEs present in an industry-region is likely to be driven by previous performance, and thus previous employment levels. A second potentially problematic aspect relates to the fact that the presence of multinationals may, by itself, induce a positive effect on employment within the same sector-region. As multinationals tend to be larger in terms of employment, it cannot be excluded that their presence may by construction lead to a higher level of sectoral employment. We address both these concerns in two robustness checks: firstly, we construct a Bartik-type of instrumental variable (IV) and re-estimate our models using two-stage panel data techniques; secondly, we test our results looking at non-MNE employment in a subsample of industry-regions.

We start with our IV strategy. Since the main explanatory variables are likely to be endogenous, we construct a apply an IV strategy using a shift-share Bartik instrument (Faggio and Overman, 2014; Crescenzi et al., 2015; Ascani and Gagliardi, 2015). The aim of the insturment is approximate the number of multinationals present in each industry-region group, excluding the effect of characteristics specific to the group itself which may drive the location choices of MNEs. For doing this we compute the instrument for the (log) number of MNEs following Equation 7:

$$\text{iv\_b\_nor\_eu}_{i,r,t} = \frac{num\_firms\_2006_{i,r}}{\sum_r num\_firms\_2006_{i,r}} * \left(\sum_r num\_MNE_{i,r,t} - num\_MNE_{i,r,t}\right) \quad (7)$$

In the formula above, *i* refers to the industry and *r* to the region to whom the region belongs. The instrument essentially redistributes the number of MNEs in sector *i* (excluding from the count the MNEs in sector *s* in region *r*) according to the respective share of firms in the sector *i* in region *r* in 2006. The exclusion of the number of MNEs in the region (the second term in Equation 7) helps addressing the problem of endogeneity (Faggio and Overman, 2014). Besides, exploiting the within region-industry variation over time in our instruments reduces the concerns for using the potentially endogenous share of firms by sector in 2006 (the first term in Equation 7).

Generally speaking, estimating IV regressions with more than one endogenous variable is complicated and generally adviced against (Agrinst and Pischke, 2009). In our case, the number of potentially endogenous variables, the similarity of two instruments and the different industrial and regional dimensions to cut our sample across make the IV estimation especially problematic. Given these challenges, and considering that reverse-casuality may be a problem for espectially intra-industry effects, we focus robustness checks on endogeneity only on Model 1[5].

TABLE 5 (IV) + TABLES WITH FIRST STAGE ESTIMATION

Table 5 reports the estimates and the statistics referring to IV estimation. The F-tests reported at the bottom of the table are all above the rule of thumb threshold of 10, usually applied in the literature, thus indicating the validity of the chosen instrument.

[5] We tried also adopting a similar strategy for instrumenting for the number of MNEs in related industries, by interacting the instrument *iv_b_nor_eu* with the previously computed relatedness matrix (Bloom et al., 2013). Whereas the instrumental variable estimations appear to work solidly for Model 1, the same is not true for Model 2: once both endogenous variables are included, the instruments jointly perform poorly.

Overall, the results shown in Table 5 provide a more solid confirmation of the conclusions reached in the previous analyses. Whereas the second stage coefficients are not found to be significant in the whole sample and in the low-knowledge industries, the effects of MNE presence on employment in the same industry are positive significant for high-knowledge sectors and KIBS. The positive effects and the sectoral heterogeneity find solid evidence in our IV estimates, even though the size of the coefficients suggest a stronger effect in regions with higher per capita income, unlike in Table 3.

With respect to the second issue (non-MNE employment), we perform the same analysis as in Tables 3 and 4, this time looking only at employment in non-multinational firms. To implement this robustness check, we use information from Orbis to compute the level of employment in each industry-region accruing to firms which are not foreign-owned. Because of the low reliability of information for certain countries (Kalemli-Ozcan et al. 2015), due to the missing information on firm-level employment, we restrict the sample of region considered in our robustness check[6]. More precisely, we select regions in countries for which the minimum correlation between data on employment in each industry according to Orbis and Eurostat SBS is 70%[7]. Having selected only countries with highly reliable data, we compute the (log) number of employees in nationally owned firms and re-estimate Models 1 and 2 once again. Both models are also estimated for the high-knowledge, low-knowledge and KIBS industries, whereas we do not group the regions along the per capita income categories due to the reduced heterogeneity in the regions included in the sample for this robustness check.

TABLE 7, 8 (NON-MNE EMPLOYMENT)

[6] It should be noticed that, whereas the firm level information on employment in Orbis may have missing values, the analysis so far has been carried out using ownership information, which does not suffer from the same problem.

[7] This implies that if even in one sector in one region, a country has correlation lower than 70%, it will not be included in the analysis. Finally, region-industries within the following 19 countries are included in the robustness check: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Hungary, Lithuania, Latvia, Luxembourg, Norway, Poland, Portugal, Romania, Slovenia, Slovakia Spain and Sweden.

Table 7 and Table 8 reproduce the results for the robustness checks on non-MNE employment. Even though the regional dimension had to be ignored, the estimates on the reduced sample of countries highlight positive significant relations between *MNE_num* and *MNE_num_rel*, from the one hand, and non-MNE employment on the other. Such positive significant relations therefore confirm the positive effect of MNEs. Besides, it is interesting to notice how, in line with the previous literature on local firm productivity (Javorcik, 2004), the inter-industry effect of MNE presence appears to be stronger than the intra-industry ones. Also, the results for non-MNE employment indicate a similar pattern in terms of industrial heterogeneity: the estimated coefficients for both *MNE_num* and *MNE_num_rel* are larger for the knowledge intensive part of the economy than for low-knowledge industries and the sample as a whole.

The robustness checks provide a general confirmation of our conclusions. Our instrumental variable strategy, based on a Bartik-type of instrument, confirms the existence of positive intra-industry spillovers, as well as their stronger effects in the case of more knowledge intensive industries. Whereas we are not able to apply the same instrumental variable method to Equation 2, due to the presence of multiple endogenous variables, we would expect the robustness of the results for Model 1 to bear on the estimates of Model 2. As a further check on the solidity of our results, we briefly look at the effect of MNE presence on non-MNE employment. Whereas we perform this check on a smaller sample of regions, the existence of positive MNE spillovers both intra- and inter-industry is confirmed. Hypotheses 3 and 4 theorize a stronger effect of MNEs for advanced industries and for regions with lower per capita income. Hypothesis 3 proves to be accurate. High-knowledge sectors and knowledge intensive services consistently show higher and more significant coefficients for MNE presence, both within and across industries. Results are less clear-cut when investigating regional heterogeneity. From our standard panel results, less advanced EU regions seem to benefit more than other areas from presence of foreign companies (hypothesis 4). However, once we implement our instrumental variable strategy, the size of the coefficients indicates a stronger effect in the case of regions with per capita income above the EU average.

CONCLUSIONS

The cross-sectoral effect of MNEs and the existence of preconditions for the local economy to benefit from foreign companies are nowadays well-established facts. The present paper contributes to this debate in two main ways. First, it shows that cross-sectoral externalities related to MNE presence transcend vertical input-output linkages in which current economic literature confine them (Javorcik, 2004; 2013). While a limitation of this study is undoubtedly the use of relatively aggregated data at the second digit of NACE classification, the positive results obtained by our relatedness-based measures at such aggregate level suggest that input-output relations are not the only channels through which knowledge spillovers take place. Second, in this paper we try to disentangle the heterogeneous effects of MNEs by linking them to sectoral and regional differences. Our results suggest that these sources of heterogeneity have to be adequately taken into account in order to better grasp the mechanics of MNE externalities. We show that within- and cross-sector linkages to foreign company are particularly important for knowledge intensive industries (with relative high degrees of absorptive capacity) and for low-income regions.

Nonetheless, some limitations emerge from our study. The lack of more disaggregated data forced us to perform the analysis based on 68 2-digit NACE sectors. This implies different potential shortcomings. First, our intra-regional spillovers are by definition rather broad, potentially encompassing what other researchers have been able to capture as cross-sectoral linkages. As argued above, this represents a limitation for this study, though it also reinforces our critique to the use of mere input-output relations as channels for knowledge spillovers. If some effects of relatedness are found across broadly defined sectors, even stronger results may be found using relatedness in more disaggregated settings. Second, in this paper we account for endogeneity issues as much as possible by using IV estimation strategies. The use of sector-region fixed effects and different types of control variables also reduce our concerns. A methodology capturing IV-estimation at both stages of estimation is difficult, while still worthwhile to pursue. Thirdly, the use of employment as a dependent variable, although suggested by theory in a consistent way, may also be considered a limitation, in that it reduces the comparability of our results with other studies in the literature. In this sense, while looking at employment effects of MNEs is very relevant in a period of economic turbulence, replicating our study using models focused on productivity will represent an important additional test for our conclusions. Relations between employment and productivity (over the life-cycle of industries and products) then have to be taken into account.

It is worth highlighting some emerging venues for further research. First of all, both theoretical and empirical investigations are needed to understand through what channels, other than input-output relations, MNE spillovers may take place. For instance, relatedness literature tends to stress cognitive and technological similarity (in labour mobility for instance) as *media* for knowledge externalities. These types of linkages have arguably found little attention in international business literature. Secondly, industrial heterogeneity should also be explored more thoroughly, in particular analyzing with greater level of details what sectors are more prone to benefit from the presence of foreign firms. Recent contributions in regional economics and economic geography have stressed the importance of institutions in affecting the behavior of actors and the functioning of the local economy (Acemoglu and Robinson, 2012; Cortinovis et al., 2017; Rodriguez-pose, 2013). Obtaining further insights on how different local conditions may affect knowledge, employment and productivity externalities of MNEs would provide valuable elements to the discussion both in the academia and policy circles.

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Table 3: Model 1 (ENDOGENOUS) - Intra-industry effects of MNE presence

	Whole sample	Low-knowledge industries			High-knowledge industries			KIBS		
VARIABLES	Employment - All	Employment - LKI	Employment - Above av. Reg. - LKI	Employment - Below av. Reg. - LKI	Employment - HKI	Employment - Above av. Reg. - HKI	Employment - Below av. Reg. - HKI	Employment - KIBS	Employment - Above av. Reg. - KIBS	Employment - Below av. Reg. - KIBS
MNE_num (ln)	0.0427***	0.0266**	0.0149	0.0325*	0.0744***	0.0446**	0.0935***	0.0736***	0.0435*	0.0940***
	(0.0113)	(0.0113)	(0.0134)	(0.0170)	(0.0164)	(0.0199)	(0.0234)	(0.0177)	(0.0232)	(0.0253)
No_MNE (dummy)	-0.0127	-0.00301	0.0163	-0.0174	-0.0259*	-0.0233	-0.0257	-0.0162	-0.0121	-0.0208
	(0.0130)	(0.0199)	(0.0247)	(0.0291)	(0.0143)	(0.0247)	(0.0177)	(0.0169)	(0.0288)	(0.0209)
HK_tert	0.952***	1.063***	0.866**	1.311**	0.947**	0.861*	0.960	1.096**	1.227**	0.926
	(0.340)	(0.374)	(0.408)	(0.608)	(0.458)	(0.485)	(0.760)	(0.523)	(0.556)	(0.912)
TotR&D	0.0107	0.00833	0.0149	-0.00159	0.0130	0.0319**	-0.0115	0.00511	0.0191*	-0.0128
	(0.00915)	(0.00869)	(0.0107)	(0.0105)	(0.0121)	(0.0132)	(0.0158)	(0.0112)	(0.00988)	(0.0189)
GDP (ln)	0.393***	0.424***	0.485***	0.392**	0.278	0.461***	0.212	0.258	0.506**	0.155
	(0.137)	(0.135)	(0.133)	(0.166)	(0.173)	(0.162)	(0.218)	(0.159)	(0.213)	(0.204)
PhK (ln)	0.0763***	0.0484**	0.0768*	0.0345	0.128***	0.0919**	0.133***	0.173***	0.0974**	0.191***
	(0.0198)	(0.0220)	(0.0415)	(0.0273)	(0.0325)	(0.0356)	(0.0447)	(0.0448)	(0.0481)	(0.0631)
Firm_num (ln)	0.0940***	0.0748***	0.0560***	0.0964***	0.138***	0.0950***	0.180***	0.169***	0.128***	0.192***
	(0.00800)	(0.00765)	(0.00745)	(0.0127)	(0.0133)	(0.00903)	(0.0180)	(0.0194)	(0.0184)	(0.0238)
MNE_emp_sp (ln)	0.00419***	0.00210***	0.00368***	0.00108	0.0114***	0.0132***	0.00915***	0.0106***	0.0127***	0.00876***
	(0.000742)	(0.000782)	(0.00106)	(0.00109)	(0.00207)	(0.00335)	(0.00262)	(0.00221)	(0.00295)	(0.00310)
Observations	75,547	46,501	18,535	27,966	29,046	12,235	16,811	20,732	8,776	11,956
R-squared	0.026	0.024	0.021	0.027	0.038	0.042	0.041	0.040	0.048	0.040
Number of id	15,515	9,574	3,770	5,804	5,941	2,474	3,467	4,233	1,773	2,460
Sector_region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year 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

Table 4: Model 2 (ENDOGENOUS) – Intra- and inter-industry effects of MNE presence

	Whole sample	Low-knowledge industries			High-knowledge industries			KIBS		
VARIABLES	Employment - All	Employment - LKI	Employment - Above av. Reg. - LKI	Employment - Below av. Reg. - LKI	Employment - HKI	Employment - Above av. Reg. - HKI	Employment - Below av. Reg. - HKI	Employment - KIBS	Employment - Above av. Reg. - KIBS	Employment - Below av. Reg. - KIBS
MNE_num (ln)	0.0299***	0.0193*	0.0187	0.0179	0.0566***	0.0478**	0.0632***	0.0577***	0.0503**	0.0641***
	(0.00898)	(0.0103)	(0.0133)	(0.0151)	(0.0134)	(0.0201)	(0.0181)	(0.0151)	(0.0233)	(0.0201)
MNE_num_rel (ln)	0.0248***	0.0163**	-0.00947	0.0326***	0.0277**	-0.00514	0.0495***	0.0232**	-0.0102	0.0462***
	(0.00823)	(0.00734)	(0.00776)	(0.00987)	(0.0110)	(0.00781)	(0.0166)	(0.0110)	(0.00840)	(0.0176)
No_MNE (dummy)	-0.0118	-0.00232	0.0160	-0.0157	-0.0252*	-0.0236	-0.0259	-0.0162	-0.0126	-0.0225
	(0.0130)	(0.0199)	(0.0246)	(0.0291)	(0.0143)	(0.0246)	(0.0176)	(0.0169)	(0.0288)	(0.0208)
HK_tert	0.823**	0.977***	0.947**	1.250**	0.801*	0.895*	0.825	0.976*	1.297**	0.824
	(0.345)	(0.370)	(0.393)	(0.609)	(0.464)	(0.493)	(0.760)	(0.517)	(0.568)	(0.912)
TotR&D	0.0110	0.00861	0.0148	-0.000335	0.0132	0.0320**	-0.00880	0.00541	0.0194*	-0.00939
	(0.00906)	(0.00869)	(0.0107)	(0.0106)	(0.0119)	(0.0133)	(0.0158)	(0.0108)	(0.0101)	(0.0188)
GDP (ln)	0.378***	0.414***	0.485***	0.374**	0.264	0.458***	0.181	0.243	0.498**	0.120
	(0.135)	(0.134)	(0.132)	(0.163)	(0.170)	(0.163)	(0.214)	(0.158)	(0.215)	(0.205)
PhK (ln)	0.0753***	0.0481**	0.0773*	0.0378	0.126***	0.0913**	0.133***	0.173***	0.0940*	0.188***
	(0.0196)	(0.0222)	(0.0416)	(0.0280)	(0.0314)	(0.0355)	(0.0424)	(0.0438)	(0.0476)	(0.0600)
Firm_num (ln)	0.0935***	0.0746***	0.0555***	0.0940***	0.137***	0.0946***	0.173***	0.166***	0.128***	0.184***
	(0.00760)	(0.00760)	(0.00756)	(0.0127)	(0.0123)	(0.00926)	(0.0149)	(0.0179)	(0.0184)	(0.0202)
MNE_num_sp (ln)	0.00423***	0.00215***	0.00364***	0.00111	0.0114***	0.0132***	0.00919***	0.0110***	0.0125***	0.00960***
	(0.000740)	(0.000782)	(0.00106)	(0.00109)	(0.00207)	(0.00335)	(0.00260)	(0.00217)	(0.00296)	(0.00303)
Observations	75,547	46,501	18,535	27,966	29,046	12,235	16,811	20,732	8,776	11,956
R-squared	0.027	0.024	0.021	0.028	0.040	0.042	0.044	0.041	0.048	0.043
Number of id	15,515	9,574	3,770	5,804	5,941	2,474	3,467	4,233	1,773	2,460
Sector_region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year 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

Table 5: Model 1 (IV) - Intra-industry effects of MNE presence

	Whole sample	Low-knowledge industries			High-knowledge industries			KIBS		
VARIABLES	Employment - All	Employment - LKI	Employment - Above av. Reg. - LKI	Employment - Below av. Reg. - LKI	Employment - HKI	Employment - Above av. Reg. - HKI	Employment - Below av. Reg. - HKI	Employment - KIBS	Employment - Above av. Reg. - KIBS	Employment - Below av. Reg. - KIBS
MNE_num (ln)	0.189	0.0754	-0.0620	0.200	0.479**	0.598*	0.381***	0.421**	0.387	0.390***
	(0.131)	(0.145)	(0.261)	(0.180)	(0.191)	(0.356)	(0.148)	(0.204)	(0.374)	(0.145)
No_MNE (dummy)	-0.00380	0.000442	0.0117	-0.00417	-0.00707	0.0139	-0.0170	-0.00365	0.00649	-0.0139
	(0.0147)	(0.0214)	(0.0286)	(0.0310)	(0.0174)	(0.0355)	(0.0187)	(0.0188)	(0.0361)	(0.0215)
HK_tert	0.846**	1.027***	0.947*	1.245**	0.694	0.429	0.876	0.873	0.923	0.858
	(0.368)	(0.393)	(0.539)	(0.605)	(0.528)	(0.751)	(0.766)	(0.563)	(0.704)	(0.912)
TotR&D	0.0109	0.00827	0.0154	-0.000422	0.0150	0.0340***	-0.00980	0.00898	0.0223**	-0.00944
	(0.00901)	(0.00868)	(0.0109)	(0.0103)	(0.0120)	(0.0126)	(0.0160)	(0.0115)	(0.00952)	(0.0200)
GDP (ln)	0.388***	0.422***	0.479***	0.387**	0.261	0.592***	0.185	0.226	0.577**	0.115
	(0.135)	(0.134)	(0.133)	(0.163)	(0.171)	(0.178)	(0.211)	(0.157)	(0.224)	(0.200)
PhK (ln)	0.0910***	0.0739***	0.0564***	0.0912***	0.129***	0.0927***	0.168***	0.154***	0.121***	0.176***
	(0.00816)	(0.00789)	(0.00762)	(0.0133)	(0.0129)	(0.00919)	(0.0175)	(0.0202)	(0.0187)	(0.0242)
Firm_num (ln)	0.0744***	0.0473**	0.0798*	0.0348	0.128***	0.106**	0.133***	0.180***	0.128**	0.189***
	(0.0197)	(0.0222)	(0.0434)	(0.0275)	(0.0317)	(0.0441)	(0.0433)	(0.0448)	(0.0624)	(0.0618)
MNE_emp_sp (ln)	0.00307***	0.00165	0.00449	-0.000358	0.0105***	0.0142***	0.00787***	0.0104***	0.0140***	0.00770**
	(0.00119)	(0.00158)	(0.00297)	(0.00192)	(0.00214)	(0.00356)	(0.00270)	(0.00227)	(0.00342)	(0.00318)
Observations	75,506	46,466	18,525	27,941	29,040	12,232	16,808	20,729	8,774	11,955
R-squared	0.019	0.023	0.018	0.018	-0.007	-0.082	0.022	0.007	-0.002	0.020
Number of id	15,474	9,539	3,760	5,779	5,935	2,471	3,464	4,230	1,771	2,459
Sector_region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F Test	13.21***	10.75***	7.239***	9.797***	30.92***	13.47***	50.12***	26.11***	9.244***	42.73***
F P-val	0.000335	0.00119	0.00829	0.00209	6.64e-08	0.000381	0	6.23e-07	0.00298	8.71e-10

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: First stage for regressions in Table 5

VARIABLES	(1) Firm - All (MNE_num (ln))	(2) HKI - All (MNE_num (ln))	(3) HKI - Above av. Reg. (MNE_num (ln))	(4) Low tech - Below av. Reg. (MNE_num (ln))	(5) HKI - All (MNE_num (ln))	(6) HKI - Above av. Reg. (MNE_num (ln))	(7) HKI - Below av. Reg. (MNE_num (ln))	(8) KIBS - All (MNE_num (ln))	(9) KIBS - Above av. Reg. (MNE_num (ln))	(10) KIBS - Below av. Reg. (MNE_num (ln))
iv_b_nor_eu	0.00134***	0.00111***	0.000587***	0.00296***	0.00325***	0.00191***	0.0143***	0.00300***	0.00163***	0.0141***
	(0.000369)	(0.000339)	(0.000218)	(0.000946)	(0.000585)	(0.000520)	(0.00202)	(0.000587)	(0.000535)	(0.00216)
No_MNE (dummy)	-0.0618***	-0.0716***	-0.0601***	-0.0806***	-0.0483***	-0.0697**	-0.0317**	-0.0384***	-0.0567**	-0.0253*
	(0.00916)	(0.0124)	(0.0201)	(0.0158)	(0.0137)	(0.0273)	(0.0138)	(0.0142)	(0.0271)	(0.0153)
HK_tert	0.674*	0.705**	1.013**	0.397	0.493	0.659	0.179	0.472	0.732	0.102
	(0.346)	(0.334)	(0.502)	(0.389)	(0.402)	(0.557)	(0.534)	(0.455)	(0.575)	(0.666)
TotR&D	-0.00103	0.00168	0.00623	-0.00654	-0.00401	-0.00294	-0.00323	-0.00990	-0.00823	-0.00760
	(0.00456)	(0.00505)	(0.00548)	(0.00848)	(0.00578)	(0.00719)	(0.00864)	(0.00728)	(0.00945)	(0.0109)
GDP (ln)	0.0328	0.0376	-0.0734	0.0279	0.0380	-0.231	0.0901	0.0816	-0.209	0.114
	(0.0814)	(0.0801)	(0.157)	(0.0866)	(0.0942)	(0.145)	(0.112)	(0.120)	(0.168)	(0.150)
Firm_num (ln)	0.0209***	0.0188***	0.00535	0.0322***	0.0234***	0.00392	0.0395***	0.0423***	0.0189	0.0549***
	(0.00469)	(0.00440)	(0.00536)	(0.00660)	(0.00761)	(0.00799)	(0.0110)	(0.00916)	(0.0132)	(0.00985)
PhK (ln)	0.0129	0.0208	0.0407	-0.00283	-0.000668	-0.0236	0.00222	-0.0176	-0.0827	0.0220
	(0.0166)	(0.0182)	(0.0274)	(0.0196)	(0.0208)	(0.0355)	(0.0249)	(0.0394)	(0.0633)	(0.0489)
MNE_emp_sp (ln)	0.00731***	0.00909***	0.0104***	0.00817***	0.00114	-0.00260	0.00212	-0.000389	-0.00439**	0.00117
	(0.000681)	(0.000825)	(0.00119)	(0.00111)	(0.00124)	(0.00197)	(0.00154)	(0.00144)	(0.00217)	(0.00186)
Observations	75,506	46,466	18,525	27,941	29,040	12,232	16,808	20,729	8,774	11,955
Number of reg_ind	15,474	9,539	3,760	5,779	5,935	2,471	3,464	4,230	1,771	2,459
Sector_region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year 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

Table 7: Model 1 (ENDOGENOUS) - Intra-industry effects of MNE presence on non-MNE employment

	Whole sample	Low-knowledge industries	High-knowledge industries	KIBS
VARIABLES	Non-MNE employment- All	Non-MNE employment - LKI	Non-MNE employment - HKI	Non-MNE employment - KIBS
MNE_num (ln)	0.0863***	0.0714***	0.110***	0.120***
	(0.0258)	(0.0263)	(0.0374)	(0.0396)
No_MNE (dummy)	-0.00190	-0.0125	0.0136	0.0117
	(0.0248)	(0.0308)	(0.0430)	(0.0505)
HK_tert	1.087	1.023	1.199*	1.529**
	(0.727)	(0.827)	(0.678)	(0.751)
TotR&D	-0.0140	-0.0163	-0.0105	-0.0202
	(0.0107)	(0.0113)	(0.0134)	(0.0142)
GDP (ln)	0.0614	0.166	-0.128	-0.282
	(0.246)	(0.252)	(0.282)	(0.302)
PhK (ln)	0.348***	0.322***	0.405***	0.571***
	(0.0705)	(0.0815)	(0.0747)	(0.0965)
Firm_num (ln)	0.0326*	0.0488**	0.00335	-0.00884
	(0.0194)	(0.0231)	(0.0197)	(0.0208)
MNE_emp_sp (ln)	-0.000177	0.000500	-0.00295	-0.00766**
	(0.00111)	(0.00122)	(0.00267)	(0.00306)
Observations	26,980	16,895	10,085	7,165
R-squared	0.041	0.049	0.033	0.040
Number of id	5,426	3,403	2,023	1,438
Sector_region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Model 2 (ENDOGENOUS) – Intra- and inter-industry effects of MNE presence on non-MNE employment

	Whole sample	Low-knowledge industries	High-knowledge industries	KIBS
VARIABLES	Non-MNE employment- All	Non-MNE employment	Non-MNE employment	Non-MNE employment
MNE_num (ln)	0.0466**	0.0394*	0.0584*	0.0746**
	(0.0194)	(0.0234)	(0.0299)	(0.0331)
MNE_num_rel (ln)	0.0544***	0.0490***	0.0608***	0.0499***
	(0.0121)	(0.0146)	(0.0136)	(0.0146)
No_MNE (dummy)	-0.00440	-0.0146	0.0100	0.00555
	(0.0250)	(0.0311)	(0.0423)	(0.0500)
HK_tert	0.589	0.604	0.567	0.944
	(0.725)	(0.808)	(0.722)	(0.774)
TotR&D	-0.0125	-0.0158	-0.00707	-0.0155
	(0.0113)	(0.0116)	(0.0142)	(0.0147)
GDP (ln)	0.0890	0.183	-0.0818	-0.242
	(0.215)	(0.234)	(0.230)	(0.261)
PhK (ln)	0.329***	0.310***	0.377***	0.535***
	(0.0630)	(0.0758)	(0.0648)	(0.0845)
Firm_num (ln)	0.0242	0.0428*	-0.00958	-0.0164
	(0.0204)	(0.0239)	(0.0202)	(0.0214)
MNE_num_sp (ln)	2.83e-05	0.000596	-0.00236	-0.00611**
	(0.00110)	(0.00123)	(0.00261)	(0.00301)
Observations	26,980	16,895	10,085	7,165
R-squared	0.049	0.056	0.044	0.048
Number of id	5,426	3,403	2,023	1,438
Sector_region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Model 1 (IV) - Intra-industry effects of MNE presence on non-MNE employment

	Whole sample	Low-knowledge industries	High-knowledge industries	KIBS
VARIABLES	Non-MNE employment- All	Non-MNE employment	Non-MNE employment	Non-MNE employment
MNE_num (ln)	-0.764	-1.675	0.719***	0.645***
	(0.912)	(2.316)	(0.221)	(0.219)
No_MNE (dummy)	-0.0385	-0.0815	-0.00557	-0.000459
	(0.0531)	(0.154)	(0.0300)	(0.0339)
HK_tert	1.358	2.759	-0.0694	0.488
	(1.816)	(4.499)	(0.864)	(0.901)
TotR&D	0.00216	0.0160	0.0138	0.0141
	(0.0224)	(0.0290)	(0.0257)	(0.0180)
GDP (ln)	-0.0118	-0.00249	-0.0515	-0.0233
	(0.269)	(0.485)	(0.231)	(0.274)
PhK (ln)	0.189***	0.191*	0.169***	0.178***
	(0.0506)	(0.111)	(0.0186)	(0.0174)
Firm_num (ln)	0.246**	0.207	0.256***	0.345***
	(0.107)	(0.163)	(0.0691)	(0.108)
MNE_emp_sp (ln)	0.0110	0.0206	-0.00228	0.00184
	(0.00893)	(0.0232)	(0.00383)	(0.00428)
Observations	25,214	15,811	9,403	6,674
R-squared	-0.222	-1.148	-0.015	0.042
Number of id	5,317	3,337	1,980	1,405
Sector_region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Under identification				
F	1.950	0.783	6.500**	6.827**
F P-val	0.166	0.379	0.0126	0.0106

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: First stage for regression s in Table 9				
	(1)	(2)	(3)	(4)
VARIABLES	Firm - All (MNE_num (ln))	HKI - All (MNE_num (ln))	HKI - All (MNE_num (ln))	KIBS - All (MNE_num (ln))
iv_b_nor_eu	0.000619	0.000349	0.00465**	0.00492***
	(0.000444)	(0.000395)	(0.00182)	(0.00188)
No_MNE (dummy)	-0.0523***	-0.0643***	-0.0360	-0.0373
	(0.0177)	(0.0238)	(0.0275)	(0.0314)
HK_tert	1.588**	1.767***	1.215	1.667*
	(0.652)	(0.640)	(0.750)	(0.900)
TotR&D	-0.00332	0.00544	-0.0185*	-0.0360***
	(0.00799)	(0.00987)	(0.00969)	(0.0129)
GDP (ln)	-0.0400	-0.0457	-0.0782	-0.135
	(0.251)	(0.257)	(0.255)	(0.257)
Firm_num (ln)	0.0519***	0.0471***	0.0598***	0.0542***
	(0.00866)	(0.00909)	(0.0110)	(0.0108)
PhK (ln)	0.0620	0.0465	0.0996*	0.204*
	(0.0436)	(0.0427)	(0.0590)	(0.105)
MNE_emp_sp (ln)	0.00928***	0.00974***	0.00640***	0.00632**
	(0.00114)	(0.00131)	(0.00219)	(0.00247)
Observations	25,214	15,811	9,403	6,674
Number of reg_ind	5,317	3,337	1,980	1,405
Sector_region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1

Table 1.A – Appendix: List of sectors		
High-knowledge=**Advanced manufacturing** +Knowledge-intensive services	Low Knowledge	
20	5	37
21	6	38
26	7	39
27	8	41
28	9	42
29	10	43
30	11	45
50	12	46
51	13	47
58	14	49
59	15	52
60	16	53
61	17	55
62	18	56
63	19	68
69	22	77
70	23	79
71	24	81
72	25	82
73	31	95
74	32	
75	33	
78	35	
80	36	

Table 2.A – Appendix: List of regions by income groups									
Above EU Average in GDP per capita				**Below EU average in GDP per capita**					
AT12	DE72	HU10	PT17	AT11	ES11	FR81	ITI2	RO21	UKK3
AT13	DE73	IE02	RO32	BE22	ES12	FR83	ITI3	RO22	UKK4
AT21	DE91	ITC1	SE11	BE32	ES13	GR11	LT00	RO31	UKL1
AT22	DE92	ITC2	SE12	BE33	ES41	GR12	LV00	RO41	UKL2
AT31	DE94	ITC3	SE21	BE34	ES42	GR13	MT00	RO42	UKM2
AT32	DEA1	ITC4	SE22	BE35	ES43	GR14	NL12	SE31	UKM3
AT33	DEA2	ITH1	SE23	BG31	ES52	GR21	NL13	SI01	UKM6
AT34	DEA3	ITH2	SE32	BG32	ES53	GR22	NL23	SI02	UKN0
BE10	DEA4	ITH3	SE33	BG33	ES61	GR23	NL34	SK02	
BE21	DEA5	ITH4	SK01	BG34	ES62	GR24	PL11	SK03	
BE23	DEB1	ITH5	UKD6	BG41	FI19	GR25	PL21	SK04	
BE24	DEB3	ITI1	UKH1	BG42	FI1C	GR30	PL22	UKC1	
BE25	DEC0	ITI4	UKH2	CY00	FI1D	GR41	PL31	UKC2	
BE31	DED5	LU00	UKI1	CZ02	FR21	GR42	PL32	UKD1	
CZ01	DEF0	NL11	UKI2	CZ03	FR22	GR43	PL33	UKD3	
DE11	DK01	NL21	UKJ1	CZ04	FR23	HU21	PL34	UKD4	
DE12	DK03	NL22	UKJ2	CZ05	FR24	HU22	PL41	UKD7	
DE13	DK04	NL31	UKJ3	CZ06	FR25	HU23	PL42	UKE1	
DE14	DK05	NL32	UKK1	CZ07	FR26	HU31	PL43	UKE2	
DE21	ES21	NL33	UKM5	CZ08	FR30	HU32	PL51	UKE3	
DE22	ES22	NL41		DE40	FR41	HU33	PL52	UKE4	
DE23	ES23	NL42		DE80	FR42	IE01	PL61	UKF1	
DE24	ES24	NO01		DE93	FR43	ITF1	PL62	UKF2	
DE25	ES30	NO02		DEB2	FR51	ITF2	PL63	UKF3	
DE26	ES51	NO03		DED2	FR52	ITF3	PT11	UKG1	
DE27	FI1B	NO04		DED4	FR53	ITF4	PT15	UKG2	
DE30	FI20	NO05		DEE0	FR61	ITF5	PT16	UKG3	
DE50	FR10	NO06		DEG0	FR62	ITF6	PT18	UKH3	
DE60	FR71	NO07		DK02	FR63	ITG1	RO11	UKJ4	
DE71	FR82	PL12		EE00	FR72	ITG2	RO12	UKK2	

Appendix 2

The main sources used in this paper are Eurostat Structural Business Survey, Cambridge Econometrics Regional Database and Bureau Van Dijk Orbis and Zephyr databases. As for the former two sources, no significant elaboration was performed. The only exception is the nearest neighbor interpolation order to fill gaps in the data, mostly on SBS employment data and Eurostat R&D and human capital information. Besides, whereas SBS provides data on employment from 2008, we decided to exclude 2008 as, out of the 15369 observations for that year, around 4500 are flagged as potentially problematic.

The treatment of BVD data was instead more complex. Orbis database provides detail information at firm-level on sector of operation, number of employees, registration date and last available year. Zephyr instead gathers information on Merger and Acquisition (M&A) deals, reporting the name and code of the firms involved, the stake of the deal, the date, etc. Data on 18 million firms in the period 2006-2014 (from Orbis) and on more than 17,000 M&A deals between 1997 and 2014 (from Zephyr) were downloaded, cleaned and geo-coded [8] (Kalemli-Ozcan et al., 2015). Whereas Orbis provides information on whether a given firm is foreign owned or not, and with what share of ownership, only the most recent information is recorded with no historical records about ownership. In other words, past information on ownership, such as whether a given firm was already foreign-owned and when it was acquired, are not provided.

In order to overcome this obstacle, information on M&A from Zephyr was used to established when a domestic firm acquired or was acquired by a foreign company. After merging data from Zephyr and Orbis, we proceeded as follows:

1. Firms which are present in both Orbis and Zephyr are considered as MNE from the year in which the first M&A in which they were involved took place. For instance, Firm A is acquired by the MNE B in 2008: firm A becomes MNE from 2008 on.
2. Firms which are recorded as foreign in Orbis but missing in Zephyr are assumed to be MNE throughout the whole period. In this way, our dataset is also able to

[8] For our analysis we included only information on firms with unconsolidated accounts, in order to avoid introducing some bias (Kalemli-Ozcan et al. 2015; Oberhofer, 2013).

capture, at least to some extent, greenfield investments, previous M&A or deals which were not reported in Zephyr.

We exclude each firm from the dataset for the years subsequent to the last available year recorded in Orbis. For example, firm A, which was acquired by MNE B in 2008, provided information to its local chamber of commerce only until 2011. As 2011 is its last available year, firm A is considered as domestic firm in the years 2006 and 2007 (period preceding its acquisition), is counted as MNE between 2008 and 2011, and excluded from the sample in 2012 and 2013. We also considered as MNE only those firms which are owned at least at 10% by a foreign counterpart.

As a last step, firm level data from the dataset obtained after these operations have been collapsed to the second digit of NACE code, in order to be compatible with the data obtained from Eurostat SBS. As a robustness check, we compute the correlation between the employment data constructed from Orbis and the one provided by SBS. The overall correlation between the two dataset is a re-assuring, being above 75%.