Journal of Economic Geography **20** (2020) pp. 1165–1205
Advance Access Published on 4 August 2020

doi: 10.1093/jeg/lbaa010

Multinational enterprises, industrial relatedness and employment in European regions

Nicola Cortinovis *,†, *Riccardo Crescenzi* ** *and Frank van Oort****

*Department of Human Geography and Spatial Planning, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, The Netherlands
**Department of Geography and Environment, London School of Economics, Houghton Street, WC2A 2AE, UK
***Department of Applied Economics, Erasmus Universiteit Rotterdam, E building, Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands
†Correspondence to: *email* <n.cortinovis@uu.nl>

Abstract

This article investigates the link between multinational enterprises (MNEs) and employment in their host regions by cross-fertilising the literature on MNE externalities with the emerging body of research on industrial relatedness. The link between employment and MNE presence in the same and related industries is tested for European regions. The results suggest that cross-sectoral MNE spillovers are mediated through industrial relatedness and that they are positively and significantly associated with higher employment levels, independently of input–output relations. Our results indicate that regions characterised by lower factor prices are likely to benefit the most from the presence of multinationals in terms of employment, but these benefits are concentrated in high knowledge-intensive sectors, potentially fostering inequalities within less-developed economies.

Keywords: Employment, foreign direct investment, relatedness, Europe, regions
JEL classifications: O33, F22
Date submitted: 10 May 2019 **Editorial decision:** 3 April 2020 **Date accepted:** 8 April 2020

1. Introduction

The capability of firms to control and organise their activities in multiple countries and the corresponding increase in global investment flows have fostered scholarly and policy debates on multinational enterprises (MNEs) and their effects on host economies (Narula and Dunning, 2000; Fu et al., 2011; Javorcik, 2013). These impacts have received significant attention in economics, economic geography and international business. Various contributions in these fields have highlighted a number of mechanisms through which MNEs, especially when pursuing knowledge-intensive and innovative activities in the host economy (Javorcik et al., 2018), have a beneficial effect on domestic firms in terms of innovation and productivity. Based on this evidence, countries and regions across the globe have started to actively compete with each other in order to attract foreign investors (Bitzer et al., 2008; Harding and Javorcik, 2011; Narula and Pineli, 2016). At the same time, new empirical research has highlighted various potential ambiguities in the link between MNE presence and local innovation, development and wealth, shedding new light on the pre-conditions for these positive effects to materialise (Görg and Greenaway, 2004; Crespo and Fontoura, 2007).

Multinationals are often seen as key generators of innovation, accounting for a large share of global research and development (R&D) spending and possessing superior knowledge on the true competitive advantage of their host countries vis-à-vis international markets for specific products (Iammarino and McCann, 2013; Crescenzi et al., 2014; Javorcik et al., 2018). Empirical evidence indeed suggests that multinationals do transfer knowledge to their foreign affiliates (Arnold and Javorcik 2009; Brambilla, 2009; Guadalupe et al., 2012). Yet, spillover effects to domestic firms in host economies may still fail to materialise or may even be negative. On the one hand, MNEs actively protect their knowledge in order to minimise knowledge leakages in favour of domestic competitors (Alcacer and Delgado, 2016). On the other hand, competition from MNEs, both in the product and factor markets, may lower productivity and innovation efforts in domestic firms (Aitken and Harrison, 1999). These mechanisms are typically used to explain the limited evidence for positive horizontal (i.e. intra-industry) spillovers (Javorcik, 2004; Lin and Saggi, 2007; Havranek and Irsova, 2011; Javorcik et al., 2018). Differently, research has found stronger support for vertical (i.e. inter-industry following the supply chain) externalities, which are conceptually justified by the higher incentives for multinationals to provide knowledge and technological insights to their suppliers (backward spillovers) and their customers (forward spillovers; Lu et al., 2017).

The aim of this article is to add to this debate from a different perspective and explore the link between MNEs activities and local labour markets by cross-fertilising the MNE spillover literature with the growing body of research on industrial relatedness. A small stream of literature has recently emerged on this subject, mainly focussing on the impacts of industrial or technological relatedness on domestic firm innovation in developing and transition regions. Lo Turco and Maggioni (2019) show that the relatedness of the production portfolio of foreign firms correlates with the diversification into new products by domestic manufacturing firms in Turkish regions. They also observe a higher degree of complexity for new products, but conditioned upon the presence of relevant absorptive capacity of domestic firms. The article focuses on the entry of new industries in regions as dependent variable (following Cortinovis et al., 2017) and argues, in line with Hidalgo et al. (2007), that developing economies like Turkey are often poorly diversified and their economy relies on a limited number of traditional products that offer a limited contribution to long-run economic growth. Following a similar approach, Zhu et al. (2017) look at the emergence of new sources of competitive advantage in manufacturing firms in Chinese districts. They show that technological relatedness to the local export mix interacts with internal and external knowledge sources (including foreign direct investment (FDI)) to establish new entry of products. Following a similar approach, Elekes et al. (2019) analysed foreign-owned firms as agents of structural change in Hungarian regions with similar conclusions. However, these recent papers do not link their findings to economy-wide outcomes beyond the firm/industry level. Conversely, the analysis of regional employment growth takes centre stage in Boschma and Iammarino (2009): using a relatedness framework they find that related regional imports play a particularly important role in Italy (while correlations with value-added growth and labour productivity are less robust). More recently, Elekes and Lengyel (2016) analysed regional employment growth contributions of foreign and domestic firms. In a different conceptual framework, Waldkirch (2009) looks at the employment impact of FDI across sectors at the country level in Mexico.

The analysis of the local employment consequences of MNE activities in a European-wide regional perspective is still a largely under-explored area of research, notwithstanding its importance for public policies. The European Union is heavily relying on the concept of relatedness (Thissen et al., 2013; McCann 2015) to underpin its innovation, Smart Specialization and Cohesion Policy strategies. At the same time, policymakers are coming to the realisation that these strategies need to embrace the FDI and Global Value Chains fully, understanding regional development as a (global) connectivity phenomenon (Crescenzi et al., 2018, 2019). Yet, coherent conceptualisations and robust empirical evidence at the regional level on the employment–FDI nexus are still missing. The lack of consensus in the existent literature on knowledge spillover effects from FDI is magnified when it comes to employment effects. Local employment effects are the balance between competition effects and learning effects. Stronger competition might not only push weaker firms out of the market—with significant employment losses—but might also foster capital intensity in the most dynamic firms, outweighing direct job creation from new FDI. Knowledge spillovers might also improve the competitive profile of domestic firms with positive effect on their expansion and growth (also in terms of employment), but domestic technological upgrading might also lead to local job losses with the adoption of labour-saving technologies.

Therefore, the analysis of local employment growth—the direct result of relatedness as a means of knowledge transmission for MNEs—is a highly needed contribution to the literature. The European Union (EU)—encompassing a wide range of territorial conditions from less developed to frontier regions—offers an ideal testing ground for theory-driven empirical analyses, making it possible to explore the heterogeneity of these links.

In capturing local employment effects, the article furthers the current understanding of the sectoral nature of MNE effects by adopting a relatedness perspective to capture broad similarities across industries, which we consider complementary to (vertical) input–output linkages[1] traditionally explored in the literature. Considering that knowledge-intensive industries and product relatedness are generally associated with employment opportunities (Frenken et al., 2007), this article is first looking at sectoral employment in European subnational regions in relation to MNE presence both within and across related sectors. The analysis also explores the heterogeneity of these relations with reference to industrial knowledge intensity and regional development levels, reflecting the large diversity of absorptive and labour market conditions in the regions of Europe. The empirical analysis of related sectors (either in its own right or in addition to input–output relations) as mediators of MNE employment effects has not been introduced before in an EU context, but may prove beneficial for understanding spillovers and policy strategies when a convincing relation is found. The existing literature has focused on individual emerging economies (Turkey in Lo Turco and Maggioni 2019; Hungary in Elekes and Lengyel , 2016, Elekes et al., 2019; and China in Zhu et al., 2017). In so doing, it has been able to leverage firm- and product-level microdata in a single country setting, to distinguish foreign vis-à-vis domestic firm transmission channels and capability measures and track structural change in a detailed manner. In this article, the focus is on industry-level employment effects where relatedness acts as a mediator (and not as outcome variable as in the existing literature). In addition, by covering the EU in its entirety (and territorial diversity), this article can capture a wider heterogeneity of effects. Finally, special attention is given to the identification of these effects in order to exclude possible endogeneity.

1 As discussed by Hidalgo et al. (2007), relatedness captures different types of linkages and similarities driving the co-location of firms, in a way that may include but it is not limited to input–output relations. We argue and show in Table A2 in Appendix A that our relatedness measure encompasses more than input–output linkages.

The empirical results show that positive and significant cross-sectoral employment effect from MNE activities materialise among related industries. This provides an initial confirmation to the idea that industrial relatedness—possibly encompassing but not limited to I-O relations—is an important channel for employment-enhancing effects from MNE activities in European regions. While the use of relatively aggregated sectors at the EU regional level does not allow us to capture relatedness at a fine-grained level, the influence of MNEs on related industries across two-digit NACE sectors, confirms the importance of looking beyond vertical linkages when exploring the employment consequences of internationalisation. These results, however, are contingent on the modelling of both regional and industrial heterogeneity. In relation to regional and industrial heterogeneity, the results suggest, in line with previous studies (Bitzer et al., 2008; Fu, 2008; Fu et al., 2011), that inter-industry effects are not negligible and tend to be stronger in relatively less-developed regions. To address potential sources of bias in our results, we perform various robustness checks: first, we apply a Bartik-type instrument (Ascani and Gagliardi, 2015; Crescenzi et al., 2015), in combination with deep lags, to approximate the distribution of MNEs across regions and sectors, while removing region–industry-specific characteristics; secondly, we re-estimate our models considering only sectoral employment from domestic firms (i.e. non-MNEs), as previous research showed that this is an important distinction in the question where new varieties stem from and spill over into (Zhu et al., 2017; Lo Turco and Maggioni, 2019). Both robustness checks confirm the validity of our conclusions.

The article is organised as follows. In Section 2, the relevant literature on MNE externalities, their preconditions and their intra- and inter-industrial scope is reviewed, in order to derive four testable hypotheses in Section 3. Empirical strategy and data to test these hypotheses are presented in Section 4. Results and robustness tests are discussed in Section 5. The final section acknowledges some key limitations of the article and presents policy implications and directions for further research.

2. MNE spillover literature

2.1. Ambiguity of MNE effects on domestic firms

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 multiple locations (Narula and Dunning, 2000; Ernst and Kim, 2002; Iammarino and McCann, 2013). On this basis, foreign subsidiaries can bring about externalities for domestic firms, some of which may lead to higher domestic productivity and (under certain circumstances) employment growth (Javorcik, 2013; Crescenzi et al., 2015).

In the last decades, a significant body of research has studied the impact of MNE subsidiaries on their host economy (Burger et al, 2013; Perri and Peruffo, 2016; Karreman et al, 2017), with multinational companies potentially affecting, either positively or negatively, the host country. Theoretical and empirical contributions have explored the different channels through which these impacts can unfold. First, local companies can learn and imitate the technologies and procedures used by MNEs (Ernst and Kim, 2002; Crespo and Fontoura, 2007). In the same way, foreign MNE networks can also offer new insights about foreign market opportunities and relational channels, facilitating the internationalisation of domestic firms (Görg and Greenaway, 2004). Secondly, domestic firms can acquire specialised knowledge by hiring workers previously employed by MNEs (Poole, 2013). Labour 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 local labour market (Javorcik, 2013). Thirdly, the increase in competition due to MNE entry can force domestic companies to become more efficient and make better use of existing technologies and resources (Jacobs et al., 2014). 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).

2.2. Inter-industry effects: buyer–supplier linkages and industrial relatedness

In the quest for cross-sectoral MNE spillovers, most of the existing literature has identified input–output relations as the main channel through which such effects materialise (Lin and Saggi, 2007; Perri and Peruffo, 2016; Lu et al., 2017). Vertical linkages to MNEs engender productivity-enhancing effects, for instance, through increased demand for local goods or stronger competition for supplying multinationals (Javorcik, 2004, 2013; Alvarez and Lopez, 2008; Crespo et al., 2009; Javorcik et al., 2018). Besides, to guarantee certain quality or technical standards, foreign companies have the incentive to share knowledge with local producers (Ernst and Kim, 2002; Javorcik et al., 2018), through visits and periodic inspections or training programmes (Fu et al., 2011). Similar dynamics apply to forward linkages. By sourcing from MNEs, local firms may benefit from goods of higher quality or technological sophistication, which in turn may streamline their production process, fostering efficiency and productivity (Crespo and Fontoura, 2007; Javorcik, 2004). Specific knowledge might also be acquired along with the good itself 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; Javorcik et al., 2018). In general, these analyses suggest that backward linkages positively contribute to the increase in level of productivity within the local economy (Javorcik, 2004; Lin and Saggi, 2007; Bitzer et al., 2008; Crespo et al., 2009), with few exceptions (Damijan et al., 2003). Conversely, forward linkages do not have significant effects on local productivity (Crespo and Fontoura, 2007).

Within the debate on inter- and intra-sectoral MNE spillovers, types of linkages other than input–output relations have received limited attention (some exceptions: Branstetter, 2006; Kugler, 2006). This contrasts with other literatures, which consider a broader set of dimensions through which industries might be connected. In the economic geography literature, externalities emerge from the recombination of both proximate (Boschma, 2005; Frenken et al., 2007) and highly diverse types of knowledge (Jacobs, 1969; Glaeser et al., 1992). In these respects, the concept of relatedness aims at capturing how local knowledge, technologies and assets influence the possibility of knowledge recombination and diversification of the economy over time (Hidalgo et al., 2007). In other words, the opportunities to diversify and operate in new (for the region) sectors depend on the industries already present in the economy: the more two sectors are related, the easier it is for firms to re-deploy their assets, acquire new capabilities and move from one sector to the other (Hausmann and Klinger, 2007; Hidalgo et al., 2007; Boschma et al., 2013; Boschma and

Capone, 2015; Cortinovis et al., 2017). The concept of relatedness thus synthesises 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; Iammarino and McCann, 2013; Crescenzi et al., 2015), may bring about significant cross-industrial knowledge flows outside of their own supply chains. While more specialised knowledge is more difficult to be redeployed, this can still happen. For instance, technical expertise may provide valuable knowledge and insights to successfully operate in similar industries, as in the case of spin-off dynamics (Boschma and Wenting, 2007; Boschma and Frenken, 2011). 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.

Based on the arguments and evidence outlined above, we propose that knowledge in one sector can find useful applications also in different but related sectors, influencing their employment levels. Whereas this idea of industrial relatedness may encompass also vertical linkages (Hidalgo et al., 2007), it specifically entails the possibility of knowledge spilling over to proximate sectors outside the supply chain. The channels for knowledge spillovers already identified in the literature, such as labour 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 by connecting different but technologically or cognitively similar industries.

If knowledge flows across industries are key to understand the diffusion of MNE effects into domestic firms, the overall employment implications of these effects have remained largely unexplored in the existing literature. The ambiguity of the MNE direct local employment effects discussed in the previous section is mirrored by the ambiguity in the diffusion of local employment effects across sectors. It remains empirically under-explored how competitive pressures from MNEs coupled by the diffusion of efficiency-enhancing practices (reducing employment in domestic firms) might be counter-balanced by employment-enhancing effects associated with higher demand (domestic and through the opening of new export markets), lower input costs, diversification into related but locally unexplored markets, and product and value chain upgrading.[2]

2.3. Heterogeneity in MNE effects

The existing literature has highlighted how local conditions and MNE characteristics may affect the ability of domestic firms to benefit (or not) 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).

2 MNEs may influence industrial employment both directly (e.g. through demand effects, attracting and forming skilled labour, etc.) and indirectly (e.g. stimulating firm entry, innovation, etc.). Given our empirical approach and the nature of our data, we cannot disentangle these effects more specifically.

Among the factors, ranging from institutional and social features (Cipollina et al., 2012; Karreman et al., 2017) to MNE characteristics (Beugelsdijk et al., 2008; Neto et al., 2008), which mediate MNE presence and its effects, one of the most relevant is the technological gap between local firms and multinationals. In these respects, whereas larger differences in terms of technological endowment between domestic and foreign firms entail greater room for learning, a larger gap also entails greater investment and risk, making the assimilation of insights, processes and technologies more difficult (Kokko, 1994; Boschma, 2005; Javorcik et al., 2018). Relatedness in terms of co-occurring sectoral specialisations, shared labour inputs and skills potentially facilitates the assimilation process.

A second critical factor mediating externalities from foreign MNEs and domestic performance is ‘absorptive capacity’ (Narula and Dunning, 2000; Blomström and Kokko, 2003), conceptualised as the stock of prior knowledge (Cohen and Levinthal, 1990). The fact that firms with stronger absorptive capacity have a greater potential to benefit from MNE spillovers suggests that certain industries might have a greater potential to benefit from MNE activities. Given the greater knowledge intensity of advanced industries, both theory and empirics suggest that MNE have stronger positive impacts in more knowledge-intensive sectors (Crespo and Fontoura, 2007; Fu et al., 2011). Conversely, in low-knowledge-intensive sectors competition effects from MNEs might prevail over learning generating a negative effect on domestic activity and employment.

3. Research setting

The literature on multinational corporations and their effects on the local economy have witnessed an upsurge in recent years. However, as highlighted in the critical review of the existing evidence, some significant knowledge gaps still exist.

First, existing research has devoted limited attention to the local domestic employment consequences of MNE entry. From a conceptual standpoint, MNEs generate employment-enhancing opportunities for domestic firms but they also increase competitive pressures (on both the product and the factor markets) and tend to boost capital deepening and productivity at the expenses of local jobs. The overall net balance in terms of employment in domestic firms has remained under-explored.

Secondly, theoretical and empirical research suggests the existence of *both* intra- and inter-sectoral spillovers. Existing evidence suggests that the former are weaker given that MNE actively limits knowledge leakages to potential competitors. The latter type of effects—referring to spillovers spanning across industrial sectors—are instead associated with knowledge diffusion along the value and supply chain and have found strong empirical support. However, as the majority of research has concentrated on input–output relations as channels for spillovers, the broader linkages related to industrial proximity have been overlooked. Differently from previous contributions, we argue that insights, technologies and workers from MNE can also flow to industries that are not connected via vertical linkages but similar in terms of productive processes, skills, competences and knowledge assets.

Thirdly, because such industrial relatedness co-evolves with sectoral diversity more naturally than with specialisation, beneficial effects are expected for employment (related to early-stage product innovation) rather than for productivity (due to later-stage process innovation; Abernathy and Clark, 1985). In other words, similar to the mechanisms behind related variety (Frenken et al., 2007), relatedness-mediated spillovers are likely to mostly impact the level of employment. Even though this reasoning strongly resonates with the traditional arguments on agglomeration economies, only a very limited literature (and none on an EU-wide scale) considered the role of industrial relatedness in MNE spillovers and its potential employment effects.

Fourthly, the effects of MNEs on domestic firms are mediated and influenced by local characteristics (Ernst and Kim, 2002; Görg and Greenaway, 2004; Meyer and Sinani, 2009). The characteristics of the local labour markets in which both MNEs and domestic firms operate—in terms of human capital, knowledge or institutional conditions—shape the nature and magnitude of the employment effects. Local economic conditions affect both the creation of new jobs in response to job-enhancing shocks due to MNE entry and the capability of the local economy to absorb job losses (due to job-adverse effects of incoming MNEs). Given the considerable differences in terms of sectoral composition, industrial sophistication and overall level of development across European regions (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 employment effects of multinational corporations on industries in European regions. In our baseline models, we want to study the intra-industry role of MNE presence on local sectoral employment. Whereas it is difficult to formulate *a priori* expectations given the ambiguity in previous contributions, we envisage sectors with higher presence of foreign companies may perform better due to intra-industries externalities.

> *Hypothesis 1*: The level of employment in a given sector and region is positively related to the presence of MNEs in the same sector–region.

As argued in the previous sections, the main focus of this article is on industrial relatedness and its ability to mediate MNE spillovers across sectors, shaping employment levels. Combining the literature on inter-industry MNE spillovers, diversity externalities (Jacob, 1969; Glaeser et al., 1992; Frenken et al., 2007) and relatedness (Boschma, 2005; Hidalgo et al., 2007), in Hypothesis 2, we theorise that knowledge spillovers from foreign companies affect employment in sectors related to that of the MNE.

> *Hypothesis 2*: The level of employment in a given sector and region is positively related to the presence of MNEs in related industries in the same region.

Our final 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 and therefore in a stronger position to benefit in terms of employment from MNE presence.

> *Hypothesis 3*: The effects of MNE presence on employment, 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 more from foreign companies (Crespo and Fontoura, 2007; Javorcik, 2013). Whereas our sample gathers 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. On these bases, we hypothesise that:

> *Hypothesis 4*: The effects of MNE presence on employment, both within-industry and across-industry, are heterogenous depending on the level of development of the target region.

4. Models, methods and data

4.1. Modelling framework

This article studies short-term effects of MNE presence, both within the same industries and in related ones, on employment in the sectors within regions. The empirical investigation of this relationship poses a number of challenges from an econometric point of view, both in terms of capturing the effects on related industries, and due to endogeneity and reverse causality. In this section, we discuss our modelling choices, providing more details on endogeneity while discussing the econometric application of this article.

In Model 1, employment in each sector–region is modelled as a function of the number of MNEs active in the region/sector in the previous year as specified in Equation (1).

$$y_{i,r,t} = \alpha_{i,r} + \tau_t + \delta MNE_{num} i, r, t - 1 + \lambda no_{MNE} i, r, t - 1 + \gamma Control_{i.r,t-1} + \varepsilon_{i,r,t}, \qquad (1)$$

where $y_{i,r,t}$ stands for the level of employment (in logs) in sector i, in region r at time t, MNE 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 thus control for within-region dependence in the error terms and potential heteroscedasticity by using robust and regionally clustered errors.

Testing for Hypothesis 2, requires an 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 $\mathbf{W}$ to generate $MNE_{num}rel$. This matrix, as explained in the following sections, captures industrial proximity between industries based on the co-occurrence of pairwise sectoral specialisation.

$$\begin{aligned} y_{i,r,t} = {} & \alpha_{i,r} + \tau_t + \delta \ MNE_{num} i, r, t - 1 + \rho \ MNE_{num} rel_{i,r,t-1} + \lambda \ no_{MNE} i, r, t - 1 \\ & + \gamma \ Control_{i.r,t-1} + \varepsilon_{i,r,t}, \end{aligned} \qquad (2)$$

Finally, we test for Hypotheses 3 and 4 by splitting the sample according to different types of sectors and regions. In other words, the same models will be estimated separately for advanced manufacturing industries,[4] knowledge-intensive services and low-knowledge sectors, as well as for more prosperous EU regions and for less-developed EU regions.

4.2. Methodology

This article aims to test whether MNE regional employment effects are perceived across industries, based on a measure of pairwise industrial proximity.

---

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

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

To do 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 us to create a measure of similarity across industries at the two-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 in Appendix D). Since our analysis will focus on the period 2008–2013, we choose to use only data from 2006 in order to reduce possible endogeneity.

Following Hidalgo et al. (2007), we start by defining the sectors in which each region is specialized. We consider region r to be specialised in sector i when it's location quotient for that sector is larger than 1. In more formal terms:

$$LQ_{ir} = \left(\frac{E_{ir}/E_{*r}}{E_{i*}/E_{**}}\right), \tag{3}$$

and

$$x_{i,r} = \begin{cases} 1, & \mathit{if}\ \ LQ_{ir} > 1 \\ 0, & \mathit{otherwise} \end{cases} \tag{4}$$

Once the sectoral measure of specialisation is computed, we count how many regions are jointly specialised in sectors i and j. We then consider i and j related if the two industries tend to systematically co-locate. Our measure of relatedness is calculated as the ratio between the observed co-occurrences and a random benchmark (Van Eck and Waltman, 2009).[5] Equation 5 represents formally the computation performed:

$$\varphi_{ij} = \frac{c_{ij}}{\left[\left(\frac{S_i}{T}\right)*\left(\frac{S_j}{T-S_i}\right) + \left(\frac{S_j}{T}\right)*\left(\frac{S_i}{T-S_j}\right)\right]*\left(\frac{T}{2}\right)}, \tag{5}$$

where c_{ij} is the co-occurrence count of specialisations in sectors i and j, S_i and S_j are the total number of occurrences 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) specialisations 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.

The result of Equation 5 is a $n \times n$ $\mathbf{W}$ matrix, with n being the number of sectors in our sample. Each cell in $\mathbf{W}$ contains the 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 $\mathbf{W}$ and we set to 0 the cells with relatedness less or equal to 1 (i.e. pairs of industries which occur less or as frequently as at random). Finally, we rescale the values of the matrix to make them range between 0 and 1. Simply multiplying the relatedness matrix $\mathbf{W}$ and the

5 Appendix E discusses and motivates in more detail our choice vis-a-vis possible alternative options (e.g. standard Hidalgo relatedness, Hidalgo relatedness based on bootstrapping procedure). In Appendix E, we also show that our results are consistent across several specifications of the relatedness matrix.

sectoral vectors of MNE_{num} in each region, we generate the variable $MNE_{num}rel$, capturing relatedness-mediated effects of MNE presence. More formally:

$$MNE_{num}rel_{i,r,t} = \sum_{j \neq i} \varphi_{i,j} * MNE_{num}j, r, t. \tag{6}$$

The main intuition behind the construction of this indicator is the same as the one used in spatial econometrics for computing spatial lag variables (LeSage, 2014), with our weights capturing proximity in the industrial space rather than geographical distance. In other words, $MNE_{num}rel_{i,r,t}$ captures how exposed sector i, in region r at time t is to MNEs in related industries. Intuitively, the more exposed the sector is, the larger the chances of spillover effects from MNEs. While different in the method, this approach is conceptually close to the work of Cicerone et al. (2019 on Italian provinces.

In Figure 1, we give a direct representation of the relatedness measure captured by **W**. In Figure 1, each node represents one of the 68 industries we collected data for, and the position relative to the other nodes is based on the pairwise relatedness scores (Hidalgo et al., 2007). As shown in the legend, round nodes are low-knowledge industries (LKI), whereas square nodes represent most advanced sectors. Each of the nodes is coloured according to 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 bottom-left side of the graph, where the network relations appear to be dense. 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 spillover effects may be stronger within the knowledge-intensive part of the economy (to be tested with Hypothesis 3) compared to spillovers across sectors with various degrees of knowledge intensity. A mirroring pattern emerges on the top-right part of the graph, where mostly low-knowledge-intensive manufacturing industries locate. In spite of the fact that lower knowledge-intensity of these industries may limit MNE externalities, also in this case, the configuration suggests opportunities for cross-sectoral spillovers.

4.3. Variables and data

In order to construct our dataset, we resort to different data sources, namely Eurostat, Cambridge Econometrics (CE) and Bureau Van Dijk (BVD). Table 1 reports the sources, period and descriptive statistics of the variables (pairwise correlation among variables reported in Table A3 in Appendix B). More details on the sectors and regions included in this study are in Appendix B, while an overview on the data cleaning process for BVD data is provided in Appendix D (Kalemli-Ozcan et al., 2015).

As shown in Table 1, we resort to official data for computing our dependent variable, *Empl (ln)*. The Structural Business Survey (SBS) of Eurostat provides information for 68 two-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 analysing innovative crossover opportunities between sectors in diversified economies that are prone to spillovers from MNEs in the EU (Frenken et al., 2007; Content and Frenken, 2016). Besides, the gap in the literature on the relation between MNEs and the local employment balance, the policy relevance of MNE employment effects in a context of economic turmoil and a wave of potential relocation of

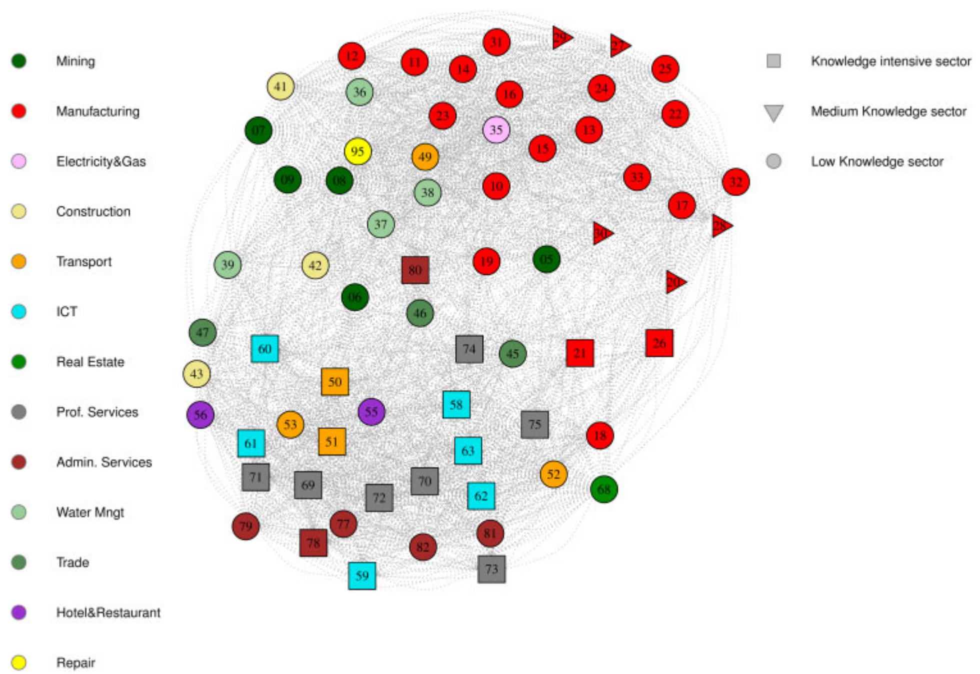

Figure 1. Network representation of relatedness.

Table 1. Descriptive statistics

Variables	Source	*N*	Mean	SD	Min	Max
Empl (ln)	Eurostat	92,309	7.729	1.822	0	13.13
MNE_num (ln)	BVD	138,528	1.108	1.377	0	8.214
MNE_num_rel (ln)	BVD	138,528	8.116	6.292	0	46.93
MNE_num_bl (ln)	BVD	138,528	1.453	1.022	0	5.328
MNE_num_fl (ln)	BVD	138,528	1.384	0.961	0	5.431
No_MNE (dummy)	BVD	138,528	0.337	0.473	0	1
HK_tert	Eurostat	136,960	0.122	0.0449	0.0366	0.328
TotR&D	Eurostat	137,520	1.526	1.229	0.0600	11.36
GDP (ln)	Eurostat	136,960	3.353	0.984	0.0751	6.242
Firm_num (ln)	Eurostat	98,014	5.466	2.003	0	11.81
PhK (ln)	CE	136,552	5.273	0.602	0.284	7.029
MNE_num_sp (ln)	BVD	138,528	69.34	37.95	0	230.9
iv_b_nor_eu	BVD	138,528	12.98	49.33	0	2436
rel_iv_b_nor_eu	BVD	138,528	96.37	130.1	0.299	1555
dl_log_f10	BVD	69,264	1.048	1.339	0	8.070
dl_rel_log_f10	BVD	69,264	7.676	6.039	0	43.34
Period				2008–2013		

international businesses following Brexit (Chen et al., 2017) makes the use of employment as the dependent variable particularly interesting and relevant.

The main variables of interests in our article 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).[6] 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. Whereas no explicit hypothesis applies to *No_MNE*,[7] the coefficient for this dummy variable can be considered of interest because it captures the average effect of hosting no foreign company.

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 percentage 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* is measured for the six 'macro' sectors available from CE. Finally, in order to control for local agglomeration economies and spatial effects, we include two variables. For each two-digit NACE industry, we include the log number of local units (*Firm_num (ln)*) to capture within-region agglomeration effects. Besides, we capture possible cross-regional effects by including the total number of MNEs (i.e. all MNEs across all industries) in the neighbouring regions (*MNE_num_sp (ln)*; Alfaro and Chen, 2014). Specifically, we compute the average of the total number of MNEs in regions sharing a border with the focal region r (LeSage, 2014).

5. Econometric analysis

The results from our baseline models are reported in Tables 2 and 3. In the tables, the heading of each column indicates whether the coefficients refer to the economy as a whole (All), to low- LKI, to high-knowledge industries (HKI)[8] or to knowledge-intensive business services (KIBS). KIBS are important knowledge-intensive facilitators of growth (Jacobs et al., 2014; Content et al., 2019) as well as generators of high-quality high-value-added jobs, which makes this group of industries interesting to focus on specifically.

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). The estimates reported in Table 2 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 positive and significant

6 We opt for using the log count of MNEs rather than the share for two main reasons. First, using shares may induce a downward bias in our estimates as suggested by Aitken and Harrison (1999) and discussed in Castellani and Zanfei (2006). To the extent that domestic firms are more susceptible to economic downturns, it would be likely to induce an increase in the share of MNEs (due to a lower denominator) with lower employment levels. Secondly, previous contributions (Altomonte and Pennings, 2009) suggest the effect of MNEs is not linear and that the effect of one additional MNE differs when moving from 0 to 1 MNEs than when moving from 100 to 101 MNEs. Log-transforming the variable helps accounting for such 'diminishing returns'.

7 The log transformation of our variable of interest would imply that region-sector observations with 0 MNE would get a missing value. After taking the logs we replace these missing values with 0, and create the *No_MNE* dummy to identify 'true zeros' (those industry–region observations with 0 MNE) from the cases of region–sectors with only 1 MNE (which become 0 once we log-transform them). We consider this a better approach to the log+1 strategy, which effectively creates a bias in the estimations. Our results are nonetheless consistent when we use either log+1, share of MNEs over total firms, share of MNE employment over total employment as measures of exposure to multinationals. For sake of brevity, the results using these alternative approaches are available on request to the authors.

8 HKI include both more advanced manufacturing and knowledge-intensive business services.

Table 2. Model 1—intra-industry effects of MNE presence

Variables	Whole sample	LKI			HKI			KIBS		
	(1) Employment —All	(2) Employment	(3) Employment —above av. Reg.	(4) Employment —below av. Reg.	(5) Employment	(6) Employment —above av. Reg.	(7) Employment —below av. Reg.	(8) Employment	(9) Employment —above av. Reg.	(10) Employment —below av. Reg.
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_num_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	8776	11,956
R^2	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	9574	3770	5804	5941	2474	3467	4233	1773	2460
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

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3. Model 2—Intra- and inter-industry effects of MNE presence

Variables	Whole sample	LKI			HKI			KIBS		
	(1) Employment—All	(2) Employment	(3) Employment—above av. Reg.	(4) Employment—below av. Reg.	(5) Employment	(6) Employment—above av. Reg.	(7) Employment—below av. Reg.	(8) Employment	(9) Employment—above av. Reg.	(10) Employment—below av. Reg.
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	8776	11,956
R^2	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	9574	3770	5804	5941	2474	3467	4233	1773	2460
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

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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 2, column 2) to high-knowledge ones and knowledge-intensive services (Columns 5 and 8). As theorised in Hypothesis 3, more knowledge-intensive parts of the economy are more strongly influenced by the presence of foreign companies and are also more prone to expand their employment levels in response to the new competitive and knowledge landscape. At the same time, sectors that 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 regional employment rates, as expected.

We investigate the role of industrial relatedness as a mediator for MNE employment effects in our last two models. Table 3 reports the estimated coefficients for Equation (2).

The estimates reported in the columns of Table 3 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 in most of the specifications. 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. The coefficients reported in Table 3 relative to the effect of MNE presence in related industries also provide valuable insights: the number of foreign companies from related industries appears to significantly impact sectoral employment. Remarkably, as for 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 except in the case of regions with above-average per capita income.

To summarise, our analysis aimed at studying the employment effects of MNE presence within and across industries, as well as across different types of sectors and regions. As a significant innovation compared to previous studies, we use industry pair co-occurrence relatedness rather than IO-relations as a framework of capturing spillovers. 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. Domestic firms in knowledge-intensive industries show the stronger potential to benefit from the presence of MNEs. Stronger positive employment effects are also concentrated in less-developed regions where the potential for learning is possibly higher and competition in the product market is lower given that both domestic firms and MNEs might be serving different (distant) markets. Less sophisticated local firms might be more oriented to the local markets while MNEs might target more the export markets benefitting from the price advantage offered by cheap labour locations.

5.1. Instrumental variable estimations

Different methodological issues may be affecting the models and results previously discussed. A first concern reflects the fact that MNE location choices are endogenous, implying that the relations found in the previous models may be biased by reverse causality.

Given the direct relation between MNE location choices and sectoral performance, this problem is likely to be especially acute in the case of intra-industry effects. Multinationals, with their location choices, self-select into region–industry pairs and their choices will be based on considerations pertaining local economic performance and availability of critical resources, either in the form of infrastructure, human capital or other (in)-tangible assets (see Crescenzi et al., 2014; Karreman et al., 2017). This implies that the number of MNEs active in an industry–region might be driven by current (or projected) performance including employment levels. The direction of the bias induced by this type of endogeneity is unknown. If MNE location choices are driven by previous region–sector performance, we would expect an upward bias in our coefficients, leading us to overstate the effect of MNE spillovers on employment. Conversely, given that MNEs tend to be more productive and innovative than local firms, they may rely less on local labour as an input for production. For instance, if MNEs are more prone to automate their production this would imply that our spillover measure and (unobservable) automation are positively correlated. As a result, the negative correlation between an omitted variable (automation) and the dependent variable (employment) would induce a downward bias in our results. Even without any strong prior on the bias of our baseline results, we address endogeneity concerns by constructing deep lags and a Bartik-type of instrumental variable (IV) and re-estimate our models using two-stage panel data techniques.

The IV strategy leverages a shift-share Bartik instrument (Faggio and Overman, 2014; Crescenzi et al., 2015). The aim of the instrument is to approximate the number of multinationals present in each industry–region group, excluding the effect of characteristics that may drive the location choices of MNEs. For this purpose, we compute the instrument for the (log) number of MNEs as specified in Equation (7):

$$\mathrm{iv_b nor_{eu}}i,r,t = \frac{num_{firms}2006_{i,r}}{\sum_r num_{firms}2006_{i,r}} * \left(\sum_r num_{MNE}i,r,t - num_{MNE}i,r,t\right) \tag{7}$$

where i refers to the industry and r to the region. The instrument redistributes the total number of MNEs (over the entire sample of EU regions) active in sector i (excluding from the count MNEs in sector i in focal region r) according to the respective share of firms in sector i in region r in 2006. Specifically, the first term of Equation (7) provides a weight based on how many firms in industry i are located in region r in 2006. This weight is interacted with the second term of Equation (7), which captures the time-varying number of MNEs in industry i across Europe, excluding those from the focal region r. Exploiting only the variation over time of the second term of our instrument drastically reduces the concerns for using the potentially endogenous share of firms by sector in 2006 (the first term in Equation 7). Besides, as our estimates rely on within variation in the sector–region dimension, the first term of Equation (6) is unlikely to violate the exclusion restriction. Similarly, the exclusion of the number of MNEs in the region (the second term in the second term in Equation 7) helps further addressing the problems with the exclusion restriction (Faggio and Overman, 2014). To test directly whether our identification strategy meets the exclusion restriction, we also use deeper lags to instrument for more recent values of our endogenous variables. Within the limits of our dataset, we maximise the time gap in our deep lagging strategy using 4-years lagged variables as instruments: for instance, the number of MNEs in 2010 was instrumented using the number of MNEs in 2006. Whereas this leads to a reduction in the number of observations included in our models, using data before the 2009 crisis is useful to increase the potential exogeneity of our instruments.

Estimating IV regressions with more than one endogenous variable is technically challenging and generally advised against (Angrist and Pischke, 2009). In our case, the number of potentially endogenous variables, the similarity of the instruments to be used and the different industrial and regional dimensions cutting across our sample, make the IV estimation especially problematic. Considering these challenges, and the fact that reverse-causality may be a problem especially for intra-industry effects, we focus our robustness checks on endogeneity of the *MNE_num (ln)* and *MNE_num_rel (ln)* variables separately.[9] Tables 4 and 5 report the estimates and the statistics referring to IV estimation. The coefficients for the first-stage regressions are reported in Appendix C.

Overall, the results shown in Table 4 provide more solid confirmation of the tentative findings presented in the previous part of the analysis. The *F*-tests reported at the bottom of Table 4 are mostly above the rule of thumb threshold of 10 (or reasonably close to it), usually applied in the literature, thus indicating the validity of the chosen instrument. Besides, the first two columns show that both our instruments are strongly relevant, which allows us to correctly overidentify the 2SLS regressions: the column marked with '(BI)' refers to the second stage using only the Bartik-type of instrument, while the column marked with '(DL)' uses the deep lagging approach. From columns 3–12 of Table 4, we use both instruments and we test whether they meet the exclusion restriction. Throughout our specifications, the Hansen *J*-test is consistently insignificant suggesting the validity of our approach. In terms of the estimated coefficients, the second-stage coefficients are not found to be significant in the whole sample and in the LKI. However, the effects of MNE presence on employment in the same industry are positive significant for high-knowledge sectors and KIBS and the pattern of sectoral heterogeneity in the effects matches the one in Table 2, with HKI and KIBS presenting bigger and more significant coefficients than LKI.[10] By comparing the coefficients in the 2SLS with the OLS regressions, the point estimates are much stronger in our robustness checks, indicating our baseline results were underestimated.

While trying to instrument for both endogenous variables at the same time strongly curbs the power of our instruments (see Footnote 4), assuming *MNE_num (ln)* as exogenous and instrumenting for *MNE_num_rel (ln)* offers a further confirmation to our results. Also in the case of Table 5, the *F*-test for the excluded instruments is above rule of thumb threshold and the Hansen *J*-test confirms the validity of our exclusion restriction. As expected from our baseline results, MNE spillovers mediated via relatedness have a significant and positive impact on sectoral employment both in the whole sample (column 3 of Table 5) and in more knowledge-intensive industries (columns 7 and 9 of Table 5).

9 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 (Javorcik et al., 2018). Whereas the IV estimations appear to work solidly for Model 1, which is not the case for Model 2: once both endogenous variables are included, the instruments do not perform as good.

10 The main difference with the baseline results is the lack of significance in the coefficient concerning LKI industries. This may suggest some selection issues which were not duly taken into account in our OLS estimates. Aspects like the introduction of policy interventions for fostering employment (e.g. the European Globalization Adjustment Fund) or industry- and location-specific MNEs attraction schemes (Crescenzi et al. 2019) are possible factors confounding OLS estimates, leading to a significant OLS coefficient. Our IVs exclude these factors (either by taking long lags or by directly excluding region–industry characteristics in the case of the Bartik instruments), therefore, the 2SLS coefficients for LKI are not as significant as before.

Table 4. Model 2 (IV)—intra-industry effects of MNE presence

Variables	Whole Sample			LKI			HKI			KIBS		
	(1) Employment —All (BI)	(2) Employment —All (DL)	(3) Employment —All	(4) Employment	(5) Employment —above av. Reg.	(6) Employment —below av. Reg.	(7) Employment	(8) Employment —above av. Reg.	(9) Employment —below av. Reg.	(10) Employment	(11) Employment —above av. Reg.	(12) Employment —below av. Reg.
MNE_num (ln)	0.189	0.229	0.242	0.0770	0.218	0.118	0.949***	0.751**	1.198***	0.936***	0.551	1.201***
	(0.131)	(0.171)	(0.160)	(0.161)	(0.290)	(0.198)	(0.279)	(0.299)	(0.345)	(0.294)	(0.343)	(0.345)
No_MNE (dummy)	−0.00380	0.0284*	0.0291*	0.0302	0.0432	0.0313	0.0544**	0.0793**	0.0244	0.0503*	0.0723*	0.0261
	(0.0147)	(0.0172)	(0.0169)	(0.0245)	(0.0484)	(0.0237)	(0.0261)	(0.0392)	(0.0288)	(0.0276)	(0.0393)	(0.0342)
Neigh. MNEs (ln)	0.00307***	0.00162	0.00157	0.00172	0.00307	−0.000364	0.00396	0.00688*	0.000598	0.00435	0.00941**	−0.00117
	(0.00119)	(0.00126)	(0.00126)	(0.00176)	(0.00310)	(0.00230)	(0.00310)	(0.00383)	(0.00439)	(0.00354)	(0.00402)	(0.00497)
Observations	75,506	46,071	46,071	28,390	11,173	17,217	17,681	7,364	10,317	12,617	5280	7337
R^2	0.019	−0.007	−0.009	0.009	−0.015	0.010	−0.252	−0.284	−0.291	−0.262	−0.158	−0.303
Number of reg_ind	15,474	15,428	15,428	9511	3747	5764	5917	2465	3452	4217	1765	2452
Sector_region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F logf10	13.21***	23.44***	18.54***	19.47***	7.391***	14.23***	14.22***	7.620***	10.21***	13.68***	6.342***	9.557***
F logf10 *p*-val	0.000335	2.20e-06	2.97e-08	1.31e-08	0.000989	2.14e-06	1.37e-06	0.000809	6.84e-05	2.24e-06	0.00250	0.000122
Hansen *J*	0	0	0.0248	0.0107	0.453	2.330	0.0822	0.0223	0.103	0.119	0.239	0.303
Hansen *p*-val	0	0	0.875	0.917	0.501	0.127	0.774	0.881	0.748	0.730	0.625	0.582

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5. Model 2 (IV)—inter-industry effects of MNE presence

Variables	Whole Sample			LKI			HKI			KIBS		
	(1) Employment —All (BI)	(2) Employment —All (DL)	(3) Employment —All	(4) Employment	(5) Employment —above av. Reg.	(6) Employment —below av. Reg.	(7) Employment	(8) Employment —above av. Reg.	(9) Employment —below av. Reg.	(10) Employment	(11) Employment —above av. Reg.	(12) Employment —below av. Reg.
MNE_num (ln)	0.0458***	0.00394	0.00274	−0.00304	−0.0223	0.00612	0.0193	0.00780	0.0498**	0.0108	0.0208	0.0412
	(0.0156)	(0.0163)	(0.0161)	(0.0225)	(0.0165)	(0.0372)	(0.0183)	(0.0276)	(0.0232)	(0.0222)	(0.0360)	(0.0270)
MNE_num_rel (ln)	−0.00595	0.0315	0.0342*	0.0153	0.0377	0.0126	0.0414*	0.00527	0.0573*	0.0321	−0.0199	0.0468
	(0.0205)	(0.0211)	(0.0203)	(0.0248)	(0.0295)	(0.0341)	(0.0227)	(0.0311)	(0.0299)	(0.0237)	(0.0373)	(0.0294)
No_MNE (dummy)	−0.0130	0.0186	0.0188	0.0269	0.0294	0.0269	0.00795	0.0234	−0.0109	0.0149	0.0445	−0.0140
	(0.0129)	(0.0144)	(0.0144)	(0.0222)	(0.0405)	(0.0223)	(0.0165)	(0.0280)	(0.0179)	(0.0200)	(0.0343)	(0.0208)
Neigh. MNEs (ln)	0.00417***	0.00270**	0.00272**	0.00234*	0.00551***	0.000294	0.00259	0.00289	0.00129	0.00221	0.00515*	−0.00120
	(0.000741)	(0.00123)	(0.00123)	(0.00141)	(0.00198)	(0.00194)	(0.00264)	(0.00298)	(0.00376)	(0.00295)	(0.00311)	(0.00428)
Observations	75,506	46,071	46,071	28,390	11,173	17,217	17,681	7,364	10,317	12,617	5280	7337
R^2	0.026	0.007	0.006	0.011	0.007	0.014	0.002	0.010	0.005	−0.001	0.017	0.002
Number of reg_ind	15,474	15,428	15,428	9511	3747	5764	5917	2465	3452	4217	1765	2452
Sector_region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F rel	27.61***	87.73***	54.01***	46.94***	17.30***	27.60***	50.44***	19.21***	30.22***	42.90***	13.46***	27.58***
F rel p-val	3.08e-07	0	0	0	3.15e-07	5.68e-11	0	7.58e-08	0	0	6.17e-06	5.78e-11
Hansen J	0	0	0.276	0.244	0.630	0.0677	0.0206	0.860	0.135	0.00798	1.183	0.326
Hansen p-val	0	0	0.600	0.621	0.428	0.795	0.886	0.354	0.713	0.929	0.277	0.568

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0$.

Also in this case, the significance and magnitude of the results are well in line with the results reported in Table 3. By comparing the results in Tables 4 and 6, we conclude there is a downward bias in the baseline regressions, though much less sizeable than in the case of Model 1.

5.2. Robustness check on domestic employment

A second potentially problematic aspect in our estimation 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. Therefore, we test our results looking at non-MNE employment in a subsample of industry–regions.

With respect to the second issue (non-MNE employment), we perform the same analysis as in Table 3, 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 that are not foreign owned. Because of the low reliability of information for certain countries (Kalemli-Ozcan et al., 2015) and due to the missing information on firm-level employment, we restrict the sample considered in our robustness check, selecting only regions in countries for which the minimum correlation between employment data in Orbis and Eurostat SBS is at least 70%.[11]

Having selected only countries with highly reliable data, we compute the (log) number of employees in domestically owned firms and re-estimate Models 1 and 2 once again. Both models are also estimated for the HKI, LKI and KIBS industries, whereas we do not group the regions along the per capita income categories due to the reduced heterogeneity in the sample for this robustness check.

Tables 6 and 7 reproduce the results for the robustness checks on non-MNE employment. The estimates on the reduced sample highlight positive significant relations between *MNE_num* and *MNE_num_rel*, from the one hand, and non-MNE employment on the other hand.

All in all, our robustness checks provide a general confirmation of our main findings. Our IV strategy, based on deep lags and 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 IV method simultaneously including within industry and relatedness mediated spillovers, we test the validity of our results instrumenting for *MNE_num_rel (ln)* alone. The results from this robustness check are in line with those obtained in our baseline regressions, suggesting that relatedness-mediated spillovers positively impact local sectoral employment. Hypotheses 3 and 4 theorise a stronger effect of MNEs for advanced industries and heterogenous effects across different levels of local development. 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

11 This implies that if even for only 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 Swede.

Table 6. Model 1—intra-industry effects of MNE presence on non-MNE employment

Variables	Whole sample Non-MNE employment—All	LKI Non-MNE employment	HKI Non-MNE employment	KIBS Non-MNE employment
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)
Observations	26,980	16,895	10,085	7165
R^2	0.041	0.049	0.033	0.040
Number of id	5426	3403	2023	1438
Sector_region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 7. Model 2—intra- and inter-industry effects of MNE presence on non-MNE employment

Variables	Whole sample Non-MNE employment—All	LKI Non-MNE employment	HKI Non-MNE employment	KIBS 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)
Observations	26,980	16,895	10,085	7165
R^2	0.049	0.056	0.044	0.048
Number of id	5426	3403	2023	1438
Sector_region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

panel results, less advanced EU regions seem to benefit more than other areas from the presence of foreign companies (Hypothesis 4).

6. 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 aim of this article is to explore the significantly under-researched link between MNEs activities and local employment at the EU-level from the perspective of industrial relatedness. Therefore, the innovative contribution of the article is 3-fold.

First, the article has unveiled a positive link between MNE presence and local employment, suggesting that internationalisation through inward FDI is a positive-sum game in Europe whereby jobs created outnumber jobs losses.

Secondly, the article offers new insights on the cross-sectoral dimension of MNE employment effects, showing that these are not limited to vertical input–output linkages (Javorcik, 2004; Alvarez and Lopez, 2008; Liang, 2017; Javorcik et al., 2018). One of the main contributions of this article is its original use of pairwise industrial relatedness, through which we capture how knowledge, technologies and assets available locally in a region influence firms' opportunities of knowledge and skill recombination. In our framework, the more two sectors are related, the easier it is for firms to re-deploy their assets, acquire new capabilities, and change, upgrade or expand their portfolio of products and therefore expand employment. In this sense, we argue that our relatedness measure captures industrial proximity in a broader sense (Boschma, 2005) than simple input–output relations. Skill relatedness (Neffke and Henning, 2013) and technological and cognitive similarities (Cortinovis et al., 2017; Farinha-Fernandes et al., 2019) in products as well as processes are likely to be the main drivers behind industrial relatedness. The positive and robust results obtained by our relatedness-based measure provide a confirmation that input–output relations do not function in isolation as channels through which MNEs influence employment in their host economies.

Thirdly, the article disentangles the heterogeneous employment effects of MNEs by linking them to sectoral and regional differences in Europe (Crescenzi and Iammarino, 2017). Our results suggest that these sources of heterogeneity have to be adequately taken into account in order to better grasp the mechanics of MNE employment effects. We show that within- and cross-sector linkages to foreign company are particularly important for knowledge-intensive industries and for low-income regions in Europe. Our results indicate that regions hosting knowledge-intensive industries and characterised by lower factor prices are likely to benefit the most from the presence of multinationals in terms of employment. In other words, we confirm the economic geography insights that economies in low-income European regions have much to gain from MNE's (Defever, 2006; Crespo and Fontoura, 2007; Javorcik, 2013, Elekes and Legyel, 2016) but we show that this is especially true in higher knowledge-intensive sectors within these economies. While MNEs can provide knowledge that can be absorbed by local (knowledge-intensive) industries (Content et al., 2019) by boosting their job-creation capabilities, building capacity for further absorption is an important precondition to achieve better overall economic performance and higher employment levels in the periphery of Europe (Cortinovis and van Oort, 2019).

These results offer a number of key insights to policymakers in Europe and beyond. In terms of place-based development strategies and policies in European regions, interregional MNE (but also trade and knowledge) network dependencies are an underexplored yet important aspect (Thissen et al., 2013). Apart from productivity-enhancing effects, the attraction of MNEs can contribute to regional job creation, especially in a relatedness framework. Whereas local and industrial conditions appear to be important, place-based policy tools such as investment promotion agencies (studied by Crescenzi et al., 2019) can significantly stimulate local employment creation through internationalisation. Importantly, our contribution also suggests that conditional on the local industrial portfolio, regional economies can leverage MNE effects in more encompassing ways than suggested by previous literature, thus facilitating sectoral revival and employment creation across the industrial space.

Intra- and inter-industry relatedness (in terms of co-occurring sectoral specialisations, shared labour inputs, IO relations and skill relatedness) facilitates the assimilation of MNEs in regional economic development, broadens the scope of regional development policies and connects our results with an emerging body of research on the regional impacts of Global Value Chain connectivity (Crescenzi et al., 2018). Building on the notion that innovation and knowledge transfer stem from the recombination and cross-over capabilities of existing and complementary knowledge and technologies (Frenken et al., 2007; Enkel et al., 2009), (regional) policy tools targeting (intra- and inter-sectoral) knowledge transfer mechanisms have the potential to enhance the MNE-employment nexus. Policies on labour mobility, education, technology transfer, public–private partnerships, tax exemptions and intellectual property rights are examples of this (Borras and Edquist, 2013) and they should be carefully assessed on their effectiveness in relation to the employment generation capacities of MNEs in own and related industries.

Nonetheless, some limitations apply to our study and its results. The lack of more disaggregated data forced us to perform the relatedness analysis based on 68 two-digit NACE sectors. This implies at least two caveats. First, our intra-regional spillovers are by definition rather broad, potentially encompassing what other researchers have been able to capture as cross-sectoral linkages. Although this represents a limitation for this study, it also highlights the possible drawbacks in the use of input–output relations as channels for knowledge spillovers. If some effects of relatedness are found across relatively broadly defined sectors, even stronger results can be expected using relatedness in more disaggregated settings. Secondly, in this article, we account for endogeneity issues as much as possible by using an IV estimation. Besides, the use of sector–region fixed effects and different types of control variables further reduces concerns for omitted variable bias. However further methodological refinements in order to fully capture causal effects deserve attention in future work (e.g. following Javorcik et al., 2018).

Funding

The research leading to these results has received funding from the European Research Council under the European Union Horizon 2020 Programme (H2020/2014-2020) (Grant Agreement no. 639633-MASSIVE-ERC-2014-STG).

References

Abernathy, W. J., Clark, K. B. (1985) Innovation: mapping the winds of creative destruction. *Research Policy*, 14: 3–22.

Aitken, B. J., Harrison, A. E. (1999) Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. *American Economic Review*, 89: 605–618.

Alcacer, J., Delgado, M. (2016) Spatial organization of firms and location choices through the value chain. *Management Science*, 62: 3213–3234.

Alfaro, L., Chen, M. (2014) The global agglomeration of multinational firms. *Journal of International Economics*, 94: 263–276.

Altomonte, C., Pennings, E. (2009) Domestic plant productivity and incremental spillovers from foreign direct investment. *Journal of International Business Studies*, 40: 1131–1148.

Alvarez, R., Lopez, R. (2008). Is exporting a source of productivity spillovers? *Review of World Economics*, 144: 723–749.

Angrist, J. D., Pischke, J.-S. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Annoni, P., Dijkstra, L., Gargano, N. (2017) The European Regional Competitiveness Index 2016. Brussels, EU Working Paper 02/2017.

Arnold, J. M., Javorcik, B. S. (2009) Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia. *Journal of International Economics*, 79: 42–53.

Ascani, A., Gagliardi, L. (2015) Inward FDI and local innovative performance. An empirical investigation on Italian provinces. *Review of Regional Research*, 35:29–47.

Beugelsdijk, S., Smeets, R., Zwinkels, R. (2008) The impact of horizontal and vertical FDI on host's country economic growth. *International Business Review* 17: 452–472.

Bitzer J., Geishecker I., and Görg H. (2008) Productivity spillovers through vertical linkages: evidence from 17 OECD countries. *Economics Letters* 99: 328–331.

Blomström, M., Kokko, A. (2003) The Economics of Foreign Direct Incentives. NBER Working Paper 9489.

Borras, S., Edquist, C. (2013) The choice of innovation policy instruments. *Technological Forecasting and Social Change*, 80: 1513–1522.

Boschma, R. (2005) Proximity and innovation: a critical assessment. *Regional Studies*, 39: 61–74.

Boschma, R., Capone, G. (2015) Institutions and diversification: related versus unrelated diversification in a varieties of capitalism framework. *Research Policy*, 44: 1902–1914.

Boschma, R., Frenken, K. (2011) The emerging empirics of evolutionary economic geography. *Journal of Economic Geography*, 11: 295–307.

Boschma, R., Iammarino, S. (2009) Related variety, trade linkages and regional growth in Italy. *Economic Geography*, 85: 289–311.

Boschma, R. A., Wenting, R. (2007) The spatial evolution of the British automobile industry: does location matter? *Industry and Corporate Change*, 16: 213–238.

Boschma, R., Minondo, A., Navarro, M (2013) The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. *Economic Geography*, 89: 29–51.

Brambilla, I. (2009) Multinationals, technology, and the introduction of varieties of goods. *Journal of International Economics*, 79: 89–101.

Branstetter, L. (2006) Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. *Journal of International Economics*, 68: 325–344.

Burger, M. J., Van der Knaap, B., Wall, R. S. (2013) Revealed competition for greenfield investments between European regions. *Journal of Economic Geography*, 13: 619–648.

Castellani, D., Zanfei, A. (2006) *Multinational Firms*, *Innovation and Productivity*. Chelthenam: Edward Elgar.

Chen, W., Los, B., McCann, P., Ortega-Argilés, R., Thissen, M., Van Oort, F. (2017) The continental divide? Exposure to Brexit in regions and countries on both sides of the Channel. *Papers in Regional Science*, 97: 25–54.

Cicerone, G.,.McCann P., Venhorst, V. A. (2019) Promoting regional growth and innovation: relatedness, revealed comparative advantage and the product space. *Journal of Economic Geography*; doi:10.1093/jeg/lbz001.

Cipollina, M., Giovannetti, G., Pietrovito, F., Pozzolo, A. F. (2012) FDI and growth: what cross-country industry data say. *The World Economy*, 35: 1599–1629.

Cohen, W. M., Levinthal D. A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35: 128–152.

Content, J., Frenken, K. (2016) Related variety and economic development: a literature review. *European Planning Studies*, 24: 2097–2112.

Content, J., Cortinovis, N., Frenken, K., Jordaan, J. (2019) Regional diversification and industry relatedness: on the importance of KIBS, GVCs & R&D. Mimeo.

Cortinovis, N., van Oort, F. (2019) Between spilling over and boiling down: network-mediated spillovers, local knowledge base and productivity in European regions. *Journal of Economic Geography*, 19: 1233–1260.

Cortinovis, N., Xiao, J., Boschma, R., Van Oort, F. (2017) Quality of government and social capital as drivers of regional diversification in Europe. *Journal of Economic Geography*, 17: 1179–1208.

Crescenzi, R., Di Cataldo, M., Giua, M. (2019) FDI inflows in Europe: does investment promotion work? LSE IGA - Institute of Global Affairs Working Paper #10/2019. Available online at:https://t.co/QlpKIRAwtQ?amp=1 [Accessed 21 April 2020].

Crescenzi, R., Harman, O., Arnold, D. (2018) Embedding and Reshaping Global Value Chains Through Investment Flows: Insights for Regional Innovation Policies. Background paper for an OECD/EC Workshop on 28 September 2018 within the workshop series "Broadening innovation policy: New insights for regions and cities", Paris.
Crescenzi, R., Gagliardi, L., Iammarino, S. (2015) Foreign multinationals and domestic innovation: intra-industry effects and firm heterogeneity. *Research Policy*, 44: 596–609.
Crescenzi, R., Pietrobelli, C., Rabellotti, R. (2014) Innovation drivers, value chains and the geography of multinational corporations in Europe. *Journal of Economic Geography*, 14: 1053–1086.
Crescenzi, R., Iammarino, S. (2017) Global investments and regional development trajectories: the missing links. *Regional Studies*, 51: 97–115.
Crespo, N., Fontoura, M. P. (2007) Determinant factors of FDI spillovers—what do we really know? *World Development*, 35: 410–425.
Crespo, N., Fontoura, M. P., Proença, I. (2009) FDI spillovers at regional level: evidence from Portugal. *Papers in Regional Science*, 88: 591–560.
Damijan, J., Knell, M., Majcen, B., Rojec, M. (2003) Technology transfer through FDI in top 10 transition countries: how important are direct effects, horizontal and vertical spillovers? William Davidson Working Paper no. 549.
Defever, F. (2006) Functional fragmentation and the location of multinationals in the enlarged *Europe. Regional Science and Urban Economics*, 36: 658–677.
Elekes, Z., Boschma, R., Lengyel, B. (2019) Foreign-owned firms as agents of structural change in regions. *Regional Studies*, 53: 1603–1613.
Elekes, Z., Lengyel, B. (2016) Related trade linkages, foreign firms and employment growth in less developed regions. Papers in Evolutionary Economic Geography 1620.
Enkel, E., Gassmann, O., Chesborough, H. (2009) Open R&D and open innovation: exploring the phenomenon. *R&D Management*, 39: 311–316.
Ernst, D., Kim, L. (2002) Global production networks, knowledge diffusion, and local capability formation. *Research Policy*, 31: 1417–1429.
Farinha-Fernandes, T., Balland, P.-A., Morrison, A., Boschma, R. (2019) What drives the geography of jobs in the US? Unpacking relatedness. *Industry and Innovation*, 26: 988–1022.
Faggio, G., Overman, H. (2014) The effect of public sector employment on local labour markets. *Journal of Urban Economics*, 79: 91–107.
Frenken, K., Van Oort, F., Verburg, T. (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41: 685–697.
Fu, X. (2008) Foreign direct investment, absorptive capacity and regional innovation capabilities. *Oxford Development Studies*, 36: 89–110.
Fu, X., Pietrobelli, C., Soete, L. (2011) The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up. *World Development*, 39: 1204–1212.
Glaeser, E., Kallal, H., Scheinkman, J., Shleifer, A. (1992) Growth in cities. *Journal of Political Economy*, 100: 1126–1152.
Görg, H., Greenaway, D. (2004) Much ado about nothing? Do domestic firms really benefit from foreign direct investment? *World Bank Research Observer*, 19: 171–197.
Guadalupe, M., Kuzmina, O., Thomas, C. (2012) Innovation and foreign ownership. *American Economic Review*, 102: 3594–3627.
Harding, T., Javorcik, B. (2011) Roll out the red carpet and they will come: investment promotion and FDI inflows. *Economic Journal*, 121: 1445–1476.
Hausmann, R., Klinger, B. (2007) The structure of the product space and the evolution of comparative advantage. CID Working Paper, No. 146. Cambridge, MA: Center for International Development, Harvard University.
Havranek, T., Irsova, Z. (2011) Estimating vertical spillovers from FDI: why results vary and what the true effect is. *Journal of International Economics*, 85: 234–244.
Hidalgo, C. A., Klinger, B., Barabàsi, A. L., Hausmann, R. (2007) The product space conditions the development of nations. *Science*, 317: 482–487.
Iammarino, S., McCann, P. (2013) *Multinationals and Economic Geography: Location, Technology and Innovation*. Cheltenham: Edward Elgar.
Jacobs, J. (1969) *The Economy of Cities*. New York: Random House.

Jacobs, W., Koster, H., Van Oort, F. G. (2014) Co-agglomeration of knowledge-intensive business services and multinational Enterprises. *Journal of Economic Geography*, 14: 443–475.

Javorcik, B. (2004) Does foreign direct investment increase the productivity of domestic firms? In search of knowledge spillovers through backward linkages. *American Economic Review*, 94: 605–627.

Javorcik B. (2013) Does FDI bring good jobs to host countries? *World Bank Research Observer*, 30: 74–94.

Javorcik, B., Lo Turco, A., Maggioni, D. (2018) New and improved: does FDI boost production complexity in host countries? *Economic Journal*, 128: 2507–2537.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., Yesiltas S. (2015) How to construct nationally representative firm level data from the ORBIS Global Database. NBER Working Paper No. 21558.

Karreman, B., Burger, M., van Oort, F. (2017) Location choices of Chinese multinationals in Europe: the role of overseas communities. *Economic Geography*, 93: 131–161.

Kugler, M. (2006) Spillovers from foreign direct investment: within or between industries? *Journal of Development Economics*, 80: 444–477.

Kokko, A. (1994) Technology, market characteristics, and spillovers, *Journal of Development Economics*, 43: 279–229.

LeSage, J. P. (2014) What regional scientists need to know about spatial econometrics. *The Review of Regional Studies*, 44: 13–32.

Liang, F.H. (2017) Does foreign direct investment improve the productivity of domestic firms? Technology spillovers, industry linkages, and firm capabilities. *Research Policy* 46: 138–159.

Lin, P., Saggi, K. (2007) Multinational firms, exclusivity, and backward linkages. *Journal of International Economics*, 71: 206–220.

Lo Turco, A., Maggioni, D. (2019) Local discoveries and technological relatedness: the role of MNEs, imports and domestic capabilities. *Journal of Economic Geography*, 19: 1077–1098.

Lu, Y., Tao, Z., Zhu, L. (2017) Identifying FDI spillovers. *Journal of International Economics*, 107: 75–90.

McCann, P. (2015) *The regional and urban policy of the European Union. Cohesion, Results-Orientation and Smart Specialisation*. Cheltenham: Edward Elgar.

Meyer, K., Sinani, E. (2009) Where and when does foreign direct investment generate positive spillovers? A meta analysis. *Journal of International Business Studies*, 40: 1075–1094.

Neffke, F., Henning, M. (2013) Skill relatedness and firm diversification. *Strategic Management Journal*, 34: 297–316.

Narula, R., Dunning, J. (2000) Industrial development, globalization and multinational enterprises: new realities for developing countries. *Oxford Development Studies*, 28: 141–167.

Narula, R., Pineli, A. (2016) Multinational enterprises and economic development in host countries: what we know and what we don't know. *John H. Dunning Centre for International Business Discussion Papers* 2016–01.

Neto, P., Brandão, A., Cerqueira, A. (2008) The impact of FDI, cross border mergers and acquisitions and greenfield investments on economic growth. FEP No. 291.

Oberhofer, H. (2013) Employment effects of acquisitions: evidence from acquired European firms. *Review of Industrial Organization*, 42: 345–363.

Perri, A., Peruffo, E. (2016) Knowledge spillovers from FDI: a critical review from the international business perspective. *International Journal of Management Reviews*, 18: 3–27.

Poole, J. (2013) Knowledge transfers from multinational to domestic firms: evidence from worker mobility. *Review of Economics and Statistics*, 95: 393–406.

Steijn, M. P. A. (2016) Improvement on the association strength: implementing probability measures based on combinations without repetition. Mimeo, Utrecht University.

Thissen, M. J. P. M., Van Oort, F. G., Diodato, D., Ruijs, A. (2013) *Regional Competitiveness and Smart Specialisation in Europe. Place-Based Development in International Economic Networks*. Cheltenham: Edward Elgar.

Van Eck, N. J., Waltman, L. (2009) How to normalize co-occurrence data? An analysis of some well-known similarity measures. *Journal of the Association for Information Science and Technology*, 60: 1635–1651.

Zhu, S., He, C., Zhou, Y. (2017) How to jump further and catch up. Path-breaking in an uneven industry space. *Journal of Economic Geography*, 17: 521–545.

Appendix

A. Relatedness and I-O matrix

One concern in relation to our definition of relatedness is that this measure would simply capture buyer–supplier relations. After all, Hidalgo et al. (2007, 482–483) directly refer to 'the inputs or outputs involved in a product's value chain (e.g., cotton, yarn, cloth, and garments)' as one of the factors potentially driving relatedness. To reduce the concerns of relatedness being simply capturing input–output linkages, we compare the pairwise relatedness score we obtained from Equation (5) with each of the national input–output matrices from the World Input–Output Database for the same year (2006). A graphic representation of the relations between the two measures of inter-industry linkages is reported in Appendix Figure A1. In the graphs in Appendix Figure A1, each dot represents one of the 4624 pairs of sectors, including the diagonal elements which are set to zero in both the relatedness and input–output matrices. As the graphs show, there is no clear association between input–output intensity and relatedness scores.

This is confirmed also by Table A1: the average correlation score across the different countries is only 0.06, with the maximum correlation being 0.1. By summing the input-output matrices across European countries, the sectoral pairwise correlation is 0.09. We consider this evidence reassuring: considering that most part of the variation in relatedness is not explained by input-output relations, we believe other approach genuinely captures forms of similarities and drivers of co-location which are other than buyer-supplier linkages.

A.1. Relatedness and/or input–output linkages?

In spite of the relatively low correlation between the relatedness and input–output weights, the concern that such our relatedness-weighted measure may simply capture buyer–supplier linkages along with cognitive and technological similarities between industries would remain. We explore this potential problem both graphically and using regression analysis. Appendix Figure A2 shows, by country, the correlation between relatedness-mediated spillovers and spillovers through backward and forward linkages. In spite of the relatively low correlation between relatedness and I-O table, the spillover measures appear to be correlated, potentially affecting the validity of our study.

To fully address this concern, and as a further identification effort of our approach, we estimate our baseline regression on industrial employment levels including the same measure of MNE spillovers applied to backward and forward linkages matrices.[12]

$$\mathrm{MNE\_num\_}bl_{i,r,t} = \sum_{j \neq i} \xi_{i,j} * \mathrm{MNE\_num}_{j,r,t}.$$

Specifically, in Appendix Table A2, we gradually expand our specification by including one at a time the variables capturing, respectively, spillovers mediated by backward linkages,

12 We compute backward and forward linkages following the standard approach in the literature, in which the intensity of relations across industries is measured as share of total production of sector i supplied to sector j (backward linkages) and the share of total purchase of sector i provided by sector k (forward linkages). In the case of backward linkages, with $\xi_{i,j}$ being the share of output of i supplied to sector j:

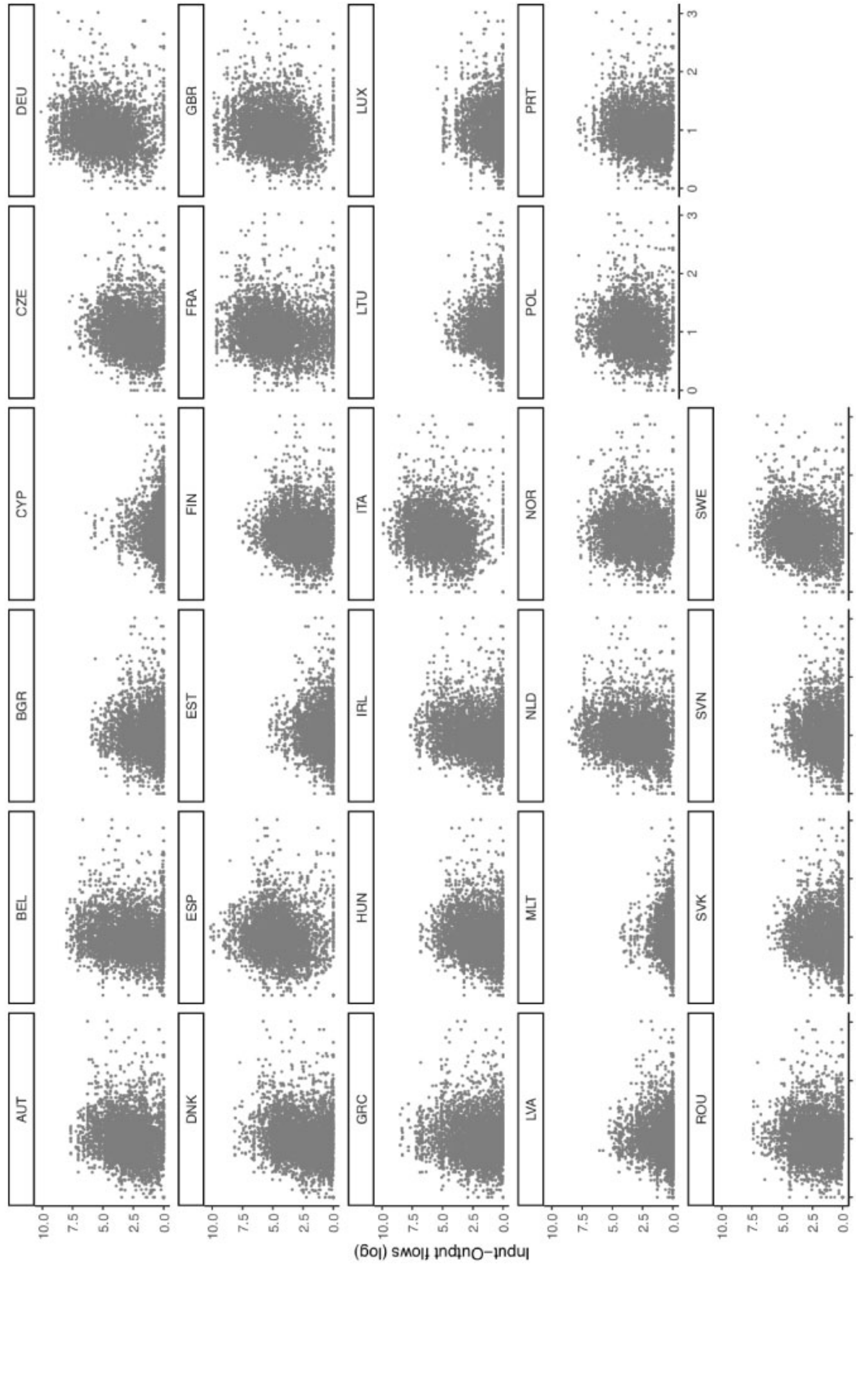

Figure A1. Correlations between relatedness scores and input–output intensity by country.

Table A1. Correlation between relatedness and national input–output matrices

Country	Correlation
Austria	0.07248859
Belgium	0.08934118
Bulgaria	0.04303621
Cyprus	0.02533528
Czech Republic	0.07352089
Denmark	0.08866313
Estonia	0.06133714
Finland	0.05600721
France	0.07532422
Germany	0.08431157
Greece	0.03813855
Hungary	0.06300398
Ireland	0.09564528
Italy	0.08906841
Latvia	0.03162895
Lithuania	0.05224235
Luxembourg	0.08319002
Malta	0.02225585
Netherlands	0.08941054
Norway	0.07974073
Polonia	0.05801462
Portugal	0.06386989
Romania	0.05993557
Slovakia	0.0556302
Slovenia	0.05888733
Spain	0.03488573
Sweden	0.10063751
United Kingdom	0.0939608
All EU	0.0908432
Average correlation	0.06569685

forward linkages and relatedness. Interestingly, we see that MNE presence is in general associated with higher levels of employment, with backward linkages appearing to dominate over forward linkages. Whereas obviously these coefficients do not capture causal effects, it is interesting to notice that our results are in line with those on productivity-enhancing MNE spillovers (Javorcik, 2004). With respect to relatedness, once we include the measure of relatedness-mediated spillovers, the coefficient for backward linkages turns insignificant while the one for relatedness is positive and strongly significant. Whereas this result should not be interpreted as the primacy of relatedness over buyer–supplier linkages, also in the light of the high correlation among the three spillover variables (cf. correlations in Appendix Table A3), it supports the idea that relatedness can capture employment spillovers in a more encompassing way, thus confirming the potential of our approach. Since our aim is not to methodologically establish the superiority of relatedness over backward linkages, and considering the likely overlap between the two spillover measures, the remainder of the analysis will focus only on relatedness and the heterogenous impacts of MNE externalities across industries and regions.

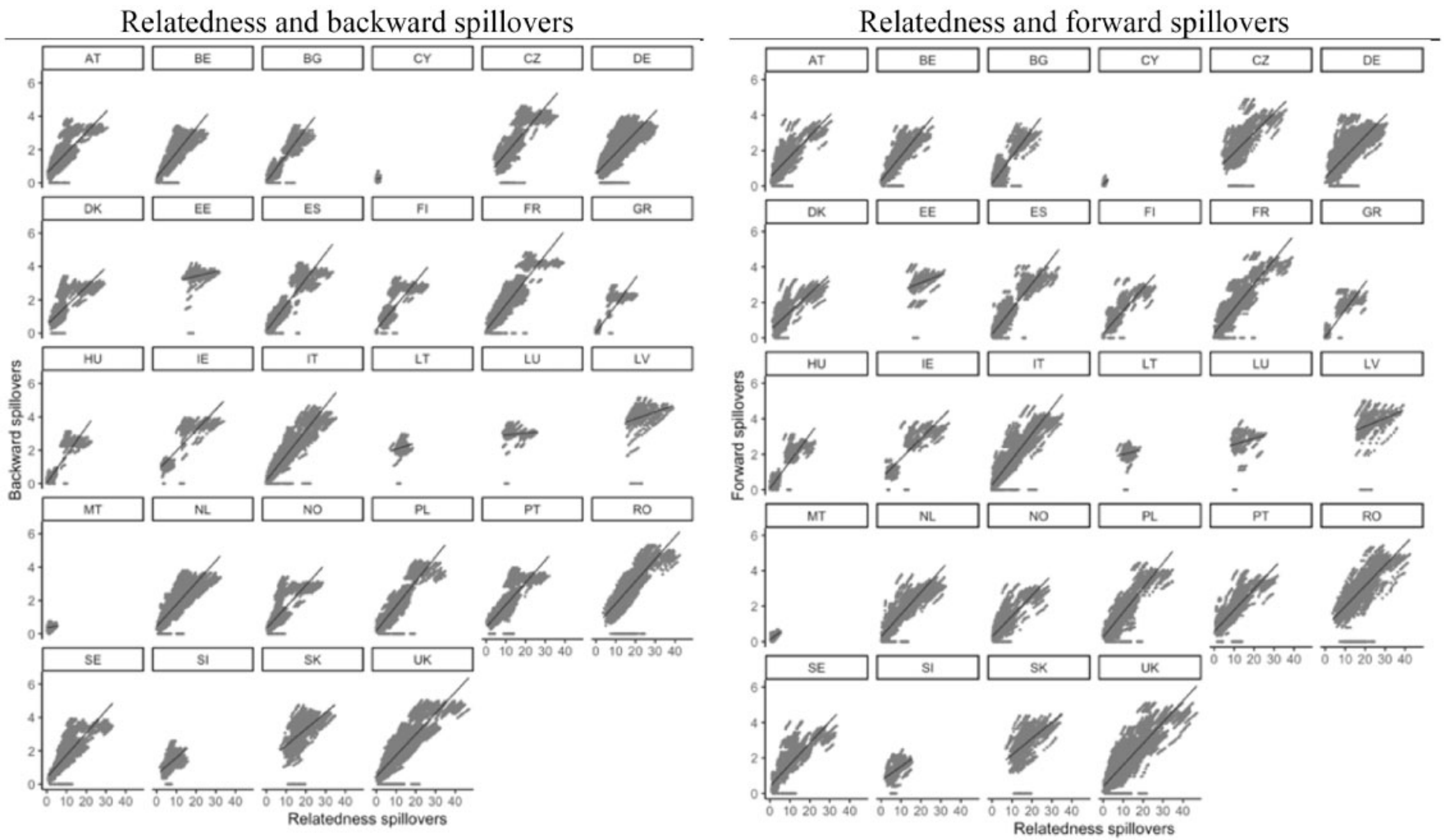

Figure A2. Correlation scores by country.

Table A2. I-O linkages, relatedness and sectoral employment levels

Variables	(1) W	(2) W+BL	(3) W+FL	(4) W+BL+FL	(5) W+RL	(6) W+BL+FL+RL
MNE_num (ln)	0.0427***	0.0333***	0.0356***	0.0331***	0.0299***	0.0300***
	(0.0113)	(0.00947)	(0.00949)	(0.00934)	(0.00898)	(0.00897)
MNE_num_bl (ln)		0.123**		0.110**		0.0120
		(0.0485)		(0.0485)		(0.0555)
MNE_num_fl (ln)			0.0986**	0.0167		−0.0255
			(0.0457)	(0.0434)		(0.0419)
MNE_num_rel (ln)					0.0248***	0.0263***
					(0.00823)	(0.00996)
No_MNE (dummy)	−0.0127	−0.0124	−0.0123	−0.0123	−0.0118	−0.0118
	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)
HK_tert	0.952***	0.879**	0.886***	0.876**	0.823**	0.825**
	(0.340)	(0.340)	(0.339)	(0.340)	(0.345)	(0.345)
TotR&D	0.0107	0.0105	0.0106	0.0105	0.0110	0.0110
	(0.00915)	(0.00893)	(0.00893)	(0.00892)	(0.00906)	(0.00911)
GDP (ln)	0.393***	0.378***	0.387***	0.379***	0.378***	0.377***
	(0.137)	(0.135)	(0.136)	(0.135)	(0.135)	(0.135)
PhK (ln)	0.0763***	0.0756***	0.0752***	0.0755***	0.0753***	0.0754***
	(0.0198)	(0.0197)	(0.0197)	(0.0197)	(0.0196)	(0.0196)
Firm_num (ln)	0.0940***	0.0934***	0.0936***	0.0934***	0.0935***	0.0936***
	(0.00800)	(0.00765)	(0.00770)	(0.00764)	(0.00760)	(0.00760)
MNE_num_sp (ln)	0.00419***	0.00453***	0.00434***	0.00452***	0.00423***	0.00423***
	(0.000742)	(0.000751)	(0.000744)	(0.000750)	(0.000740)	(0.000749)
Observations	75,547	75,547	75,547	75,547	75,547	75,547
R^2	0.026	0.027	0.027	0.027	0.027	0.027
Number of reg_ind	15,515	15,515	15,515	15,515	15,515	15,515
Sector_region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0264	0.0270	0.0268	0.0270	0.0275	0.0275

Notes: Clustered standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B. Further descriptives and data coverage

The table below (A4) provides an overview of the industries included in our sample. The codes are the two-digit industrial codes of the NACE classification, based on the 2008 revision. These have been split in low knowledge and high-knowledge sectors based on the classification provided by Eurostat[13].

Table A3. Correlation table

Variables		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Empl (ln)	**1**	1															
MNE_num (ln)	**2**	0.6	1														
MNE_num_rel (ln)	**3**	0.33	0.56	1													
MNE_num_bl (ln)	**4**	0.35	0.55	0.89	1												
MNE_num_fl (ln)	**5**	0.38	0.58	0.89	0.93	1											
No_MNE (dummy)	**6**	−0.5	−0.57	−0.38	−0.39	−0.41	1										
HK_tert	**7**	0.09	0.17	0.29	0.32	0.26	−0.13	1									
TotR&D	**8**	0.12	0.13	0.21	0.24	0.21	−0.14	0.46	1								
GDP (ln)	**9**	0.37	0.31	0.51	0.54	0.52	−0.27	0.41	0.44	1							
Firm_num (ln)	**10**	0.79	0.55	0.24	0.19	0.26	−0.39	0.02	0.04	0.24	1						
PhK (ln)	**11**	0	0.01	0.01	−0.05	−0.02	0.05	−0.19	−0.11	−0.17	0.1	1					
MNE_num_sp (ln)	**12**	0.25	0.31	0	−0.04	0	−0.18	0.01	0.01	0	0.29	0.01	1				
iv_b_nor_eu	**13**	0.31	0.48	0.21	0.19	0.2	−0.17	0.09	0.05	0.19	0.35	0.02	0.29	1			
rel_iv_b_nor_eu	**14**	0.29	0.35	0.67	0.54	0.55	−0.21	0.28	0.15	0.56	0.29	0.01	0	0.25	1		
dl_log_f10	**15**	0.6	0.98	0.55	0.54	0.57	−0.54	0.18	0.13	0.32	0.55	0.03	0.3	0.49	0.35	1	
dl_rel_log_f10	**16**	0.34	0.57	0.99	0.88	0.88	−0.37	0.32	0.21	0.53	0.24	0.04	−0.01	0.21	0.68	0.56	1

Table A4. List of sectors

High knowledge = Advanced manufacturing (in bold) + Knowledge-intensive services	Low knowledge	
20	05	37
21	06	38
26	07	39
27	08	41
28	09	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

(continued)

13 Please find the classification at this link: https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries.

Table A4.. (continued)

High knowledge = Advanced manufacturing (in bold) + Knowledge-intensive services	Low knowledge	
72	25	82
73	31	95
74	32	
75	33	
78	35	
80	36	

Table A5. 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	

Maps in Appendix Figure A3 show that, while regions with above-average income tend to be knowledge-intensive, there are various exceptions to the rule. For instance, the region of Toulouse (Midi-Pyrenees) stands out in terms of knowledge-intensity while the average income is below the EU average. The difference is even more remarkable for different Central-Eastern EU regions, such as Western Slovakia, Transdanubia regions in Hungary and Vest region in Romania.

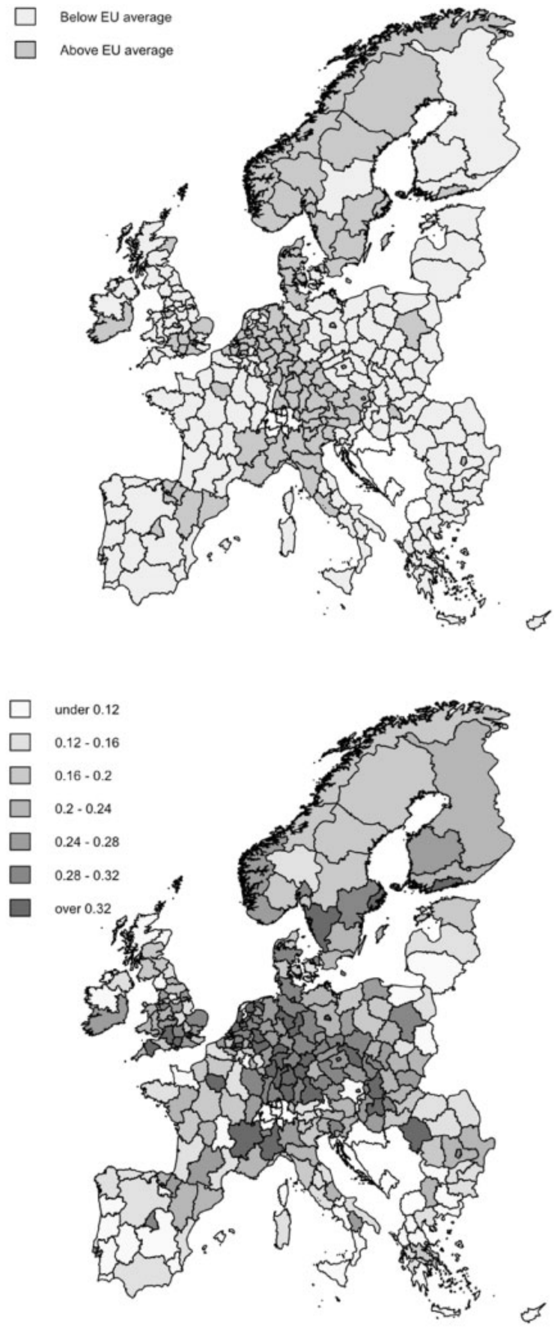

Figure A3. Maps on regions with above-average income (upper panel) and employment share in knowledge-intensive activities (lower panel).

C. First stage of IV regressions

Table A6. First-stage regressions for 2SLS in Table 4 (endogenous variable: MNE_num (ln))

Variables	(1) First stage—All	(2) First stage—All	(3) First stage—All	(4) First stage—LKI	(5) First stage —Ab av. Reg.—LKI	(6) First stage —be av. REG.—LKI	(7) First stage —HKI	(8) First stage —Ab av. Reg.—HKI	(9) First stage —Be av. Reg.—HKI	(10) First stage —KIBS	(11) First stage —Ab av. Reg.—KIBS	(12) First stage —Be av. Reg.—KIBS
iv_b_nor_eu	0.00134***		0.00128***	0.000987***	0.000496**	0.00233***	0.00364***	0.00251***	0.0118***	0.00343***	0.00230***	0.0119***
	(0.000369)		(0.000385)	(0.000331)	(0.000206)	(0.000863)	(0.000738)	(0.000652)	(0.00286)	(0.000742)	(0.000663)	(0.00310)
dl_log_f10		0.0466***	0.0445***	0.0557***	0.0414**	0.0644***	0.0185	0.0129	0.0174	0.0327*	0.0236	0.0310
		(0.00963)	(0.00971)	(0.0110)	(0.0164)	(0.0147)	(0.0152)	(0.0225)	(0.0197)	(0.0177)	(0.0277)	(0.0224)
No_MNE (dummy)	−0.0618***	−0.0592***	−0.0594***	−0.0616***	−0.0726***	−0.0504***	−0.0558***	−0.0779***	−0.0331**	−0.0439***	−0.0482*	−0.0364*
	(0.00916)	(0.0106)	(0.0107)	(0.0144)	(0.0255)	(0.0155)	(0.0159)	(0.0286)	(0.0163)	(0.0159)	(0.0252)	(0.0199)
HK_tert	0.674*	0.724**	0.672*	0.799**	1.417**	0.337	0.389	0.996	0.247	0.539	0.958	0.509
	(0.346)	(0.364)	(0.359)	(0.355)	(0.617)	(0.406)	(0.456)	(0.773)	(0.512)	(0.517)	(0.917)	(0.568)
TotR&D	−0.00103	0.00291	0.00328	0.00324	0.0100*	−0.00993	0.00409	0.00815	0.000315	0.00328	0.00773	0.00240
	(0.00456)	(0.00518)	(0.00516)	(0.00616)	(0.00549)	(0.00912)	(0.00509)	(0.00623)	(0.00948)	(0.00579)	(0.00718)	(0.0120)
GDP (ln)	0.0328	0.0279	0.0258	0.00692	−0.818***	0.0747	0.0706	−1.321***	0.255**	0.0684	−1.430***	0.213
	(0.0814)	(0.0952)	(0.0940)	(0.0909)	(0.314)	(0.0840)	(0.125)	(0.358)	(0.119)	(0.162)	(0.496)	(0.161)
Firm_num (ln)	0.0209***	0.0163***	0.0162***	0.0157***	0.0137	0.0183***	0.0169**	0.0101	0.0225***	0.0179*	0.00484	0.0312***
	(0.00469)	(0.00499)	(0.00497)	(0.00533)	(0.0135)	(0.00498)	(0.00770)	(0.0136)	(0.00820)	(0.00919)	(0.0146)	(0.00954)
PhK (ln)	0.0129	0.0243	0.0261	0.0451	0.00529	0.0436	−0.00279	−0.0342	0.0170	−0.0207	−0.0868	0.0250
	(0.0166)	(0.0323)	(0.0322)	(0.0305)	(0.0617)	(0.0348)	(0.0421)	(0.0770)	(0.0491)	(0.0534)	(0.106)	(0.0651)
Neigh. MNEs (ln)	0.00731***	0.00325***	0.00320***	0.00598***	0.00719***	0.00528***	−0.00258	−0.00600**	−0.000528	−0.00356**	−0.00694**	−0.00149
	(0.000681)	(0.000974)	(0.000975)	(0.00126)	(0.00194)	(0.00165)	(0.00160)	(0.00268)	(0.00194)	(0.00176)	(0.00307)	(0.00208)
Observations	75,506	46,071	46,071	28,390	11,173	17,217	17,681	7364	10,317	12,617	5280	7337
Number of reg_ind	15,474	15,428	15,428	9511	3747	5764	5917	2465	3452	4217	1765	2452
Sector_region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A7. First-stage regressions for 2SLS in Table 5 (endogenous variable: MNE_num_rel (ln))

Variables	(1) First stage —All	(2) First stage —All	(3) First stage —All	(4) First stage —LKI	(5) First stage —Ab av. Reg.—LKI	(6) First stage —Be av. Reg.—LKI	(7) First stage —HKI	(8) First stage —Ab av. Reg.—HKI	(9) First stage —Be av. Reg.—HKI	(10) First stage —KIBS	(11) First stage —Ab av. Reg.—KIBS	(12) First stage —Be av. Reg.—KIBS
rel_iv_b_nor_eu	0.00747***		0.00525***	0.00507***	0.00211	0.00961*	0.00524***	0.00286**	0.0124**	0.00502***	0.00256*	0.0123**
	(0.00142)		(0.00135)	(0.00155)	(0.00152)	(0.00519)	(0.00130)	(0.00131)	(0.00521)	(0.00134)	(0.00139)	(0.00580)
dl_rel_log_f10		0.317***	0.289***	0.292***	0.300***	0.302***	0.286***	0.290***	0.291***	0.285***	0.284***	0.292***
		(0.0338)	(0.0357)	(0.0372)	(0.0620)	(0.0466)	(0.0371)	(0.0713)	(0.0435)	(0.0390)	(0.0775)	(0.0457)
MNE_num (ln)	0.468***	0.371***	0.363***	0.291***	0.384***	0.185***	0.471***	0.617***	0.286***	0.559***	0.737***	0.333***
	(0.0571)	(0.0397)	(0.0389)	(0.0356)	(0.0638)	(0.0354)	(0.0537)	(0.0795)	(0.0593)	(0.0644)	(0.0937)	(0.0704)
No_MNE (dummy)	−0.0577***	−0.0836***	−0.0867***	−0.0781***	−0.0751*	−0.0575**	−0.0978***	−0.129***	−0.0392	−0.116***	−0.166***	−0.0419
	(0.0192)	(0.0186)	(0.0185)	(0.0221)	(0.0387)	(0.0229)	(0.0277)	(0.0432)	(0.0331)	(0.0346)	(0.0531)	(0.0399)
HK_tert	3.103	2.761	1.370	1.534	5.541	−0.269	1.172	4.244	0.521	0.916	3.963	0.525
	(2.114)	(2.084)	(2.018)	(1.966)	(3.492)	(2.239)	(2.249)	(4.065)	(2.668)	(2.584)	(4.775)	(3.102)
TotR&D	0.00296	0.0235	0.0339	0.0196	0.0677**	−0.0721	0.0572	0.130***	−0.0568	0.0697	0.157***	−0.0604
	(0.0291)	(0.0401)	(0.0392)	(0.0360)	(0.0310)	(0.0490)	(0.0456)	(0.0442)	(0.0575)	(0.0521)	(0.0517)	(0.0661)
GDP (ln)	0.579	−0.647	−0.661	−0.411	−6.813***	0.221	−1.128	−9.557***	−0.0240	−1.143	−10.71***	−0.122
	(0.512)	(0.600)	(0.571)	(0.509)	(1.599)	(0.475)	(0.743)	(1.965)	(0.700)	(0.899)	(2.414)	(0.970)
Firm_num (ln)	0.0321	−0.0119	−0.0128	0.00245	−0.00462	0.0168	−0.0337	−0.0801*	0.0142	−0.0391	−0.0764	0.0172
	(0.0279)	(0.0196)	(0.0193)	(0.0179)	(0.0417)	(0.0164)	(0.0289)	(0.0479)	(0.0283)	(0.0364)	(0.0542)	(0.0373)
PhK (ln)	0.0213	−0.130	−0.0755	−0.0379	−0.167	−0.0727	−0.123	−0.364	−0.0306	−0.205	−0.510	0.00169
	(0.118)	(0.168)	(0.165)	(0.160)	(0.340)	(0.169)	(0.194)	(0.332)	(0.235)	(0.259)	(0.398)	(0.352)
Neigh. MNEs (ln)	−0.00393***	−0.0111***	−0.0119***	−0.00853***	−0.0192***	0.000131	−0.0172***	−0.0301***	−0.00593*	−0.0182***	−0.0312***	−0.00525
	(0.00137)	(0.00247)	(0.00246)	(0.00215)	(0.00392)	(0.00188)	(0.00333)	(0.00530)	(0.00351)	(0.00345)	(0.00551)	(0.00343)
Observations	75,506	46,071	46,071	28,390	11,173	17,217	17,681	7364	10,317	12,617	5280	7337
Number of reg_ind	15,474	15,428	15,428	9511	3747	5764	5917	2465	3452	4217	1765	2452
Sector_region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

D. Data development

The main sources used in this article are the Eurostat SBS, 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 neighbour 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 15,369 observations for that year, around 4500 are flagged as potentially problematic.

The treatment of BVD data was instead more complex. Orbis database provides detailed 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[14] (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, is not provided.

In order to overcome this obstacle, information on M&A from Zephyr was used to establish 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 that 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 that 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 capture, at least to some extent, greenfield investments, previous M&A and 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 (after the first detected M&A), and excluded from the sample in 2012 and 2013 (since no information is reported after 2011). Besides, we considered as MNE only those firms which are owned at least at 10% by a foreign counterpart.

As the 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 datasets is a re-assuring, being above 75%.

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

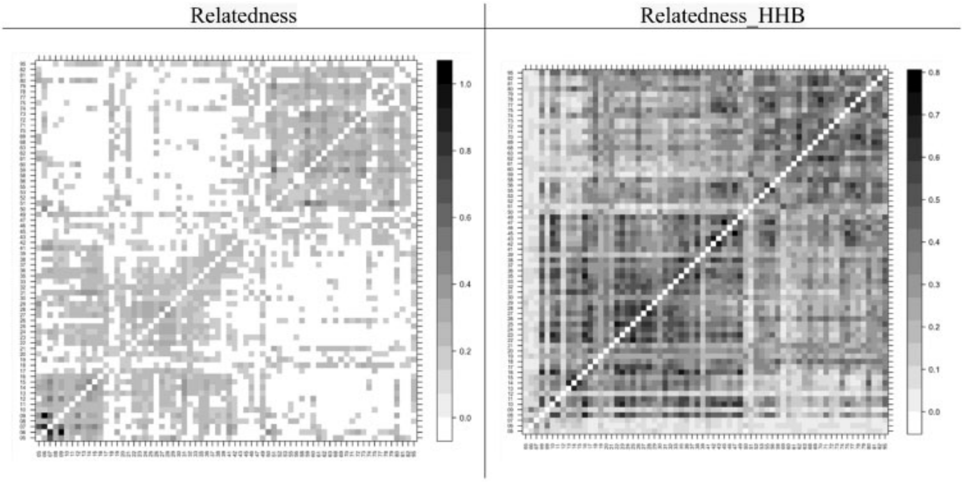

Figure A4. Comparison between different forms of relatedness.

E. Discussion and robustness of relatedness

While our analysis uses the concept of relatedness introduced by Hidalgo et al. (2007), in our empirical specification, we use a relatedness measure based on a small sample modification (Steijn, 2016) of the association measure developed by Van Eck and Waltman (2009). We compute relatedness using employment data on sectors and regions in 2006. Whereas this does not allow us to model the possible variation in industrial specialisation over time, we are convinced it is a solid approach since it reduces the source of variation to changes in the number of MNEs, rather than combining it with the change in sectoral specialisations. Besides, considering the relatively short time dimension available in our data, we believe the distribution of regional specialisations would probably change only to a limited extent. In what follows we discuss our choices with respect to the methodology applied in our article and we report a number of robustness checks using different versions of the Hidalgo measure of relatedness.

Appendix Figures A4 and A5 show the heat maps across different measures of relatedness, where 'Relatedness' refers to the one used in our analysis, 'Relatedness_HHB' refers to the measure introduced by Hidalgo et al. in their 2007 paper, and 'Relatedness_H90' and 'Relatedness_H95' are the bootstrapped version of Hidalgo relatedness using the 90th and 95th percentile as threshold for defining specialisations (see Cortinovis et al., 2017 for details). With the only exception of 'Hidalgo Relatedness', the matrices appear to capture a similar structure of relatedness, with more strongly related industries being at the bottom left, along the diagonal and in the top-right part of the heat maps. The traditional measure of relatedness shows considerably less structure, with most industries being strongly related to most other industries.

However, we have become aware of an issue undetected by previous works using bootstrapped versions of the Hidalgo relatedness, which is due to the fact that in bootstrapping procedures only regions above a certain threshold are considered as specialised. As the threshold is based on a chosen percentile, it implies that for any industry, a relatively constant number of regions are considered as specialised. This puts a cap on the number of specialised regions for each industry which, in turn, affects the actual relatedness score, since that is

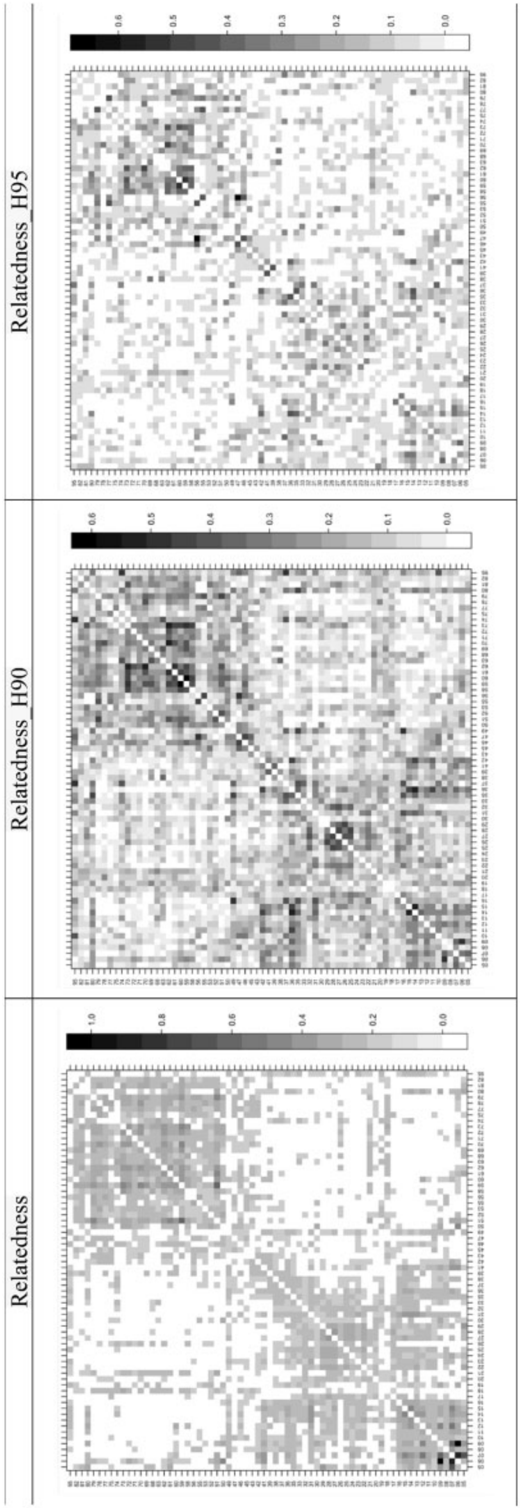

Figure A5. Comparison between different forms of relatedness (bootstrapping).

Table A8. Robustness check on different relatedness measures

Variables	(1) Employment —All—Rel	(2) Employment —All—H90	(3) Employment —All—H95	(4) Employment —All—HHB
MNE_num (ln)	0.0299***	0.0315***	0.0350***	0.0311***
	(0.00898)	(0.00906)	(0.00929)	(0.00895)
No_MNE (dummy)	−0.0118	−0.0124	−0.0126	−0.0127
	(0.0130)	(0.0130)	(0.0130)	(0.0130)
MNE_num_rel (ln)	0.0248***			
	(0.00823)			
MNE_num_h90 (ln)		0.0220***		
		(0.00821)		
MNE_num_h95 (ln)			0.0270**	
			(0.0130)	
MNE_num_hhb (ln)				0.00836**
				(0.00326)
Observations	75,547	75,547	75,547	75,547
R^2	0.027	0.027	0.027	0.027
Number of reg_ind	15,515	15,515	15,515	15,515
Control variables	Yes	Yes	Yes	Yes
Sector_region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Clustered standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

calculated as the conditional probability of being specialised in any pair of industries. This leads to the issue that the unique number of scores that the bootstrapped relatedness matrix takes is a function of the percentile used, and it is remarkably lower than using other relatedness measures. In our case, this implies that with a 95th percentile threshold we obtain 36 unique values, while with a 90th percentile threshold the unique scores of relatedness are 72. Using our preferred relatedness matrix, the number of unique values is 1079. In these respects, using the bootstrapping method has the significant drawback of effectively making the relatedness scores a categorical indicator (with 36 or 72 levels) rather than a truly continuous measure. In this sense, the association measure comparing the relatedness score with a random benchmark may have the indirect advantage of reducing the concern on how specialisation is defined. While the traditional approach of a score of the location quotient above 1 (LQ > 1) has some limitations, the association measure seems to correct, to some extent, for the case in which many regions may appear specialised. If most of the regions meet the LQ > 1 requirement, it will be implicitly more likely for two industries to appear in the random benchmark as well, making the association measure less likely to capture spurious relatedness. From our point of view, this is the most likely explanation for the difference in the structures between the relatedness measure we currently use and the standard relatedness measure by Hidalgo, which are both based on the LQ > 1 definition of specialisation.

Finally, Appendix Table A8 shows that, in spite of the differences in the matrices, the results we find are very consistent. Regardless of the measure used to capture relatedness, the different baseline specification shows a positive and significant relation between relatedness-mediated spillovers and local industrial employment.