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RESEARCH ARTICLE

Knowledge sources for Industry 4.0 technologies in European regions: the role of inward FDIs

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ABSTRACT
This study investigates the extent to which inward innovative FDIs can contribute to European regions' potential to access external knowledge useful for the development of Industry 4.0 (I4.0) technologies. By contributing to recent research on regional I4.0, we maintain that incoming multinational companies enable regions to access knowledge generated abroad that is usable for local I4.0 inventions. Using citation data about I4.0 patent applications and innovative FDIs, we estimate a gravity model that supports this idea. The knowledge base of I4.0 technologies developed in European NUTS 3 regions positively correlates with innovative inward FDIs. The correlation is driven by both greenfield FDIs and cross-border M&As, with FDIs originating outside Europe providing the greatest contribution to knowledge transfer. The findings are consistent with the relative weakness of Europe in the development of I4.0 technologies and suggest that place-based FDI policies could help European regions to overcome this gap.

KEYWORDS
Industry 4.0; foreign direct investments; regional knowledge base; digital technologies; knowledge diffusion

JEL CLASSIFICATION
O31; F23; R11

1. Introduction

Industry 4.0 (I4.0), the new industrial paradigm driven by digitalisation and automation, has become central to policy and academic agendas due to its transformative potential across sectors (Cefis et al. 2023). Alongside the green transition, the European Commission has placed the digital transition underpinning I4.0 at the heart of its 2020 Industrial Strategy, its Digital Strategy, and the National Recovery and Resilience Plans under NextGenerationEU. The recent EU vision of Industry 5.0 builds on the digitalisation path set by Industry 4.0, aiming to foster a more sustainable, human-centric, and resilient industrial future through new digital technologies (European Commission 2021; Renda, Schwaag Serger, and Tataj 2021).

While policy support for digitalisation in Europe is increasing, the geographical distribution of Industry 4.0 technologies across its regions remains fragmented, with spatial patterns revealing marked regional asymmetries in both capabilities and the knowledge sources underpinning their development (Corradini, Santini, and Vecciolini 2021; Muscio and Ciffolilli 2020). Moreover, European regions – and the EU as a whole – appear to lag behind the technological frontier in the digital domain (Guarascio and Stöllinger 2025; Van Roy, Vertesy, and Damioli 2020). These patterns raise concerns about the ability of regions to embed these new I4.0 technologies in their economic fabric and the risk that these technologies may widen economic and territorial disparities across Europe. This highlights the need for cohesive digitalisation policies, which have only recently begun to attract the attention of EU policy-makers (e.g. the Digital Europe Programme 2021–2027 and recent updates of the EU Coordinated Plan on AI). Given the complex and rapidly evolving nature of I4.0 technologies, and the limited capacity of local resources to fully cope with their development, a crucial element in this context is the ability of regions to access external knowledge and connect with leading-edge places at the global technological frontier.

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This paper explores one potential mechanism through which regions may access external knowledge critical for the development of I4.0 technologies: innovative inward foreign direct investments (FDIs). We investigate whether these FDIs are associated with the integration of foreign knowledge into local I4.0 inventions, using backward citations as a proxy for international knowledge sourcing. In this way, the paper contributes to understanding the role of innovative FDIs as conduits for cross-border knowledge flows – that is, the extent to which they facilitate regional access to technological knowledge developed abroad and embed it in I4.0 inventions developed in EU regions.

Our contribution relates to, and extends, various strands of literature. The geography of innovation literature has produced a body of work on the role of extra-regional linkages, including analyses of how international trade and foreign capital flows shape regional economic growth and learning opportunities (e.g. Iammarino 2018; Iammarino and McCann 2013). However, this strand has largely focused on the structural determinants of regions' internationalisation and regions' aggregate outcomes, often examining the effects of FDIs on the innovative performance of origin and destination locations (Castellani and Pieri 2013 and 2016; Crescenzi, Gagliardi, and Iammarino 2015 and Crescenzi, Dyèvre, and Neffke 2022; Zhu, Hey, and Zhou 2017; He, Yan, and Rigby 2018; Ascani, Balland, and Morrison 2020 and Ascani et al. 2020; Castellani, Marin, et al. 2022. Similarly, the international economics literature acknowledges the role of FDIs as vehicles for international knowledge spillovers (e.g. Branstetter 2006; Gong 2023; Keller and Yeaple 2009; van Pottelsberghe de la Potterie and Lichtenberg 2001).

Yet, the extent to which the geography of inward FDIs mirrors that of incoming international knowledge flows, and how their alignment facilitates access to prior-art knowledge for local technologies, remains empirically underexplored. This paper contributes to filling this gap by examining how the geography of inward innovative FDIs aligns with that of the foreign origins of knowledge cited in patents – thus offering a micro-level perspective on cross-border knowledge acquisition – with an application to I4.0-related technologies.

We further contribute to the extant research by providing new empirical evidence that distinguishes the role of greenfield FDIs and cross-border mergers and acquisitions (M&As) in facilitating access to foreign knowledge for the development of I4.0 technologies.

While the mechanisms of knowledge transfer may apply across different technological domains, the focus on I4.0 is particularly timely due to the general-purpose nature and the transformative and enabling potential of these technologies (Goldfarb, Taska, and Teodoridis 2023; Martinelli, Mina, and Moggi 2021). This perspective also responds to growing concerns over Europe's lag in digital innovation (Guarascio and Stöllinger 2025; Van Roy, Vertesy, and Damioli 2020) and complements emerging findings that question the capacity of European regions to leverage FDIs for local technological upgrading (Damioli and Marin 2024).

Empirically, we compile a novel dataset linking geo-referenced patent data with greenfield FDIs and cross-border M&As in metropolitan and NUTS-3 regions of the EU27 and the UK, over the period 2004–2017. I4.0-related patents are identified through keyword-based queries (as in Bianchini, Damioli, and Ghisetti 2023) and their backward citations are used to trace the international knowledge base they draw from. We then apply a gravity-type modelling approach to examine whether the presence of innovative FDIs from a given country into a region is associated with increased citation of that country's knowledge in local I4.0 patents.

Our findings show a robust positive correlation between inward innovative FDIs and foreign knowledge sourcing in EU I4.0 regional patents – especially when FDIs originate from outside the EU. This suggests that MNCs can create knowledge pipelines between their home-countries and the host EU regions, facilitating local inventors' access to critical foreign knowledge. Both greenfield investments and cross-border M&As contribute to this dynamic. These results offer insights for place-based innovation policies, highlighting the potential for targeted FDI attraction to support local technological upgrading.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature and discusses our contribution to it. Section 3 describes the data, the methodological approach, and provides some descriptive evidence. Section 4 discusses the results and Section 5 concludes.

2. Background literature

2.1. Regional development of I4.0 technologies

Having recently emerged on both academic and policy agendas, I4.0 is attracting significant attention as a digital– and automation-driven new industrial paradigm transforming firms' production, organisation, and innovation processes (Cefis et al. 2023). Recent research highlights its disruptive impact not only on firms, but also on how I4.0 techno-economic activities are organised spatially (De Propris and Bellandi 2021), affecting regional labour markets (Crowley, Doran, and McCann 2021), local digital business models, and the restructuring of value chains across regions, especially via territorial servitisation (Adler and Florida 2021; Capello and Lenzi 2021b; Vaillant et al. 2021). These dynamics challenge regions to shift their development paths and to avoid being locked into outdated industrial trajectories (Jeannerat and Theurillat 2021).

As evolutionary economic geography has widely documented, changes of local technological paths mainly rely on regions' capacity to master and leverage the new technologies underpinning paradigmatic shifts, as well as to acquire the knowledge necessary to do so. Recent research shows that the regional distribution of I4.0 technologies is quite uneven, and determined by the intersection between the distinguishing features of the individual technologies (e.g. in terms of complexity, applicability, and entry barriers) and the local capabilities required for their development (typically in terms of human skills and competencies) (Buarque et al. 2020; Corò et al. 2021; Corradini, Santini, and Vecciolini 2021). Moreover, since technological trajectories are typically characterised by strong place and path-dependence, studies on the determinants of I4.0 development have mostly focused on internal regional capabilities, like the pre-existing presence of Industry 3.0 expertise and digital competencies and skills (Balland and Boschma 2021; Capello and Lenzi 2021a; Laffi and Boschma 2022).

However, given the complexity and rapid evolution of I4.0 technologies, which often exceed the innovation capacity of local systems, this internal focus is limiting. To effectively support their development, regions must increasingly access external sources of expertise, especially from areas at the technological frontier (De Propris and Bellandi 2021). Recent firm-level evidence also supports this view. Agostino et al. (2025), for example, show that participation in global value chains enhances the likelihood of digital technology adoption in Italian manufacturing firms. External linkages should therefore be explicitly incorporated into regional analyses of I4.0 technologies. As we will illustrate below, while some of these external factors have been addressed in previous studies, important gaps remain – that this paper seeks to fill.

2.2. External knowledge linkages and global pipelines

External knowledge sources accessible to local actors are diverse in both scope and nature. Knowledge can be exchanged in embodied forms – such as through trade relationships (Andersson, Bjerke, and Karlsson 2013; Boschma and Iammarino 2009; Boschma, Martin, and Minondo 2016) or the mobility of key individuals like migrant inventors (Coda-Zabetta et al. 2022; Miguelez and Morrison 2022; Trippl 2013) – or in disembodied forms, such as collaboration in R&D projects or co-inventive activities (Abbasiharofteh, Broekel, and Mewes 2024; Wanzenböck, Scherngell, and Brenner 2014).

Among these, international knowledge transfer plays a particularly important role. Regions benefit from participating in global value chains and various forms of production and innovation networks (Chaminade and Plechero 2015; Cooke 2017; Yeung 2021). Regional innovation processes increasingly depend on the interplay between 'local buzz' – the informal exchange of knowledge among co-located actors – and 'global pipelines' that connect regions to external sources of expertise (Bathelt, Malmberg, and Maskell 2004). While local capabilities remain essential, they are no longer sufficient; international linkages among firms, entrepreneurs, and research institutions have become key drivers of regional competitiveness (Berman, Marino, and Mudambi 2020; Perri, Scalera, and Mudambi 2017). These connections allow knowledge to flow across distant locations, enriching local specialisation through access to diverse technological inputs (Neffke et al. 2018; Turkina and Van Assche 2018).

MNCs play a pivotal role in this context. By combining the benefits of spatial proximity within local clusters with those of organisational proximity in corporate networks, MNCs act as critical enablers of cross-border knowledge access (Bathelt and Li 2014, 2020). This insight has informed a broader literature on the role of inward FDIs in facilitating the transfer of external knowledge to host regions – knowledge that local actors may draw upon in their own innovation activities. Studies across economic geography, international economics, and international business have shown that inward FDIs can support local productivity growth (Gong 2023; Huang, Liu, and Xu 2012; Keller and Yeaple 2009; van Pottelsberghe de la Potterie and Lichtenberg 2001), innovation (Ascani, Balland, and Morrison 2020; Crescenzi, Dyèvre, and Neffke 2022; Crescenzi, Gagliardi, and Iammarino 2015; Fu 2008), technological specialisation (Castellani, Marin, et al. 2022), and structural change (He, Yan, and Rigby 2018; Zhu, Hey, and Zhou 2017). These effects are typically found to be heterogeneous, depending on factors such as the characteristics of the investing MNC (e.g. its collaborative approach), the type of FDI (e.g. greenfield vs. M&A; asset-seeking vs. asset-augmenting), and the absorptive capacity and internationalisation profile of host regions and firms. While these and other factors have received considerable attention, the spatial dimension of the mechanisms through which MNCs channel foreign knowledge into local contexts has been less explored – and this constitutes the core focus of our analysis.

2.3. MNCs as conduits of cross-border knowledge transfer

Extant research in economic geography and international business generally treats MNCs as knowledge carriers that bring proprietary knowledge into a host region upon entry. By doing so, MNCs create or strengthen links between the host location and the broader MNC's knowledge network – particularly that of the firm's country of origin. This perspective is in line with Cantwell and Piscitello (2015), who show that subunits of MNCs in host regions can leverage internal corporate network connections with their parent companies to facilitate access to international knowledge. Their analysis of a large sample of MNCs finds that these linkages expand the domain of knowledge search, thereby increasing the likelihood of building new areas of competence in the host economy. In a similar vein, we focus on the role of innovative FDIs in transferring home-country knowledge that can be accessed and recombined in the development of I4.0 technologies by host-region inventors.

Operationally, we measure this process by examining the extent to which local I4.0 patents cite – and thus build upon – patents originating in the home countries of MNC investors (see Section 3.1 for details on the construction of patent citations).[1] This approach is in the spirit of Branstetter (2006), who uses patent citations to trace the role of FDI in facilitating knowledge flows – specifically, from U.S. firms to Japanese investors and vice versa – with a focus on the investing firms themselves as knowledge carriers. In contrast, and in line with our knowledge conduit perspective, we focus on whether the presence of inward innovative FDIs from a given country is associated with increased use of that country's prior-art knowledge by host-region inventors in the I4.0 domain. Rather than focusing on knowledge flows within investing firms, we assess how FDI relationships enable host regions to tap into foreign knowledge generated in MNCs' countries of origin.

This approach allows us to address a key gap in the literature: the lack of direct evidence on whether and how FDI channels facilitate the concrete use of foreign knowledge in local technological development, particularly in the I4.0 domain. Using this framework, we investigate a mirroring mechanism – namely, whether the geography of knowledge spillovers reflects that of the underlying FDI channels. Specifically, we assess whether the presence of bilateral inward FDI is associated with an increased likelihood that local I4.0 patents cite inventions originating from the corresponding source country.

To our knowledge, no existing study has examined the extent to which FDIs help regions build pipelines to access non-local knowledge relevant to the local development of technologies. This is especially relevant for I4.0 technologies, as their general-purpose and enabling nature make their local effect dependent on the recombination with complementary knowledge – much of which lies beyond regional or national boundaries.

This gap in the literature is unfortunate for at least two mutually reinforcing reasons. First, the advancement of I4.0 technologies lies largely in the hands of large MNCs (Liu, Huang, and Xing 2021), which possess extensive R&D capabilities that they can deploy across their international networks

[1] Backward patent citations are widely accepted as a reliable proxy for knowledge flows between cited and citing inventions (Trajtenberg, Henderson, and Jaffe 1997).

(Grassano, Hernández Guevara, and Fako 2022). Second, external knowledge accessed through international linkages like FDIs is especially relevant for European countries and regions, which face a persistent gap with respect to global technological front-runners in I4.0 development. Since the early days of the Industry 3.0 revolution, Europe's industry has struggled to match the innovation pace set by the United States (Guarascio and Stöllinger 2025; O'Mara 2020), and this lag persists. Key innovation indicators continue to show that the EU is falling behind, with digital-related R&D and patents heavily concentrated in a small number of U.S. and Asian corporations (Van Roy, Vertesy, and Damioli 2020; UNCTAD 2021; Guarascio and Stöllinger 2025). In contrast to these global leaders, Europe continues to face structural challenges in closing the digital divide (Brattberg, Csernatoni, and Rugova 2020). In this context of intensified global competition – the so-called 'digital innovation race' (Rikap and Lundvall 2021) – inward innovative FDIs represent a crucial means for local actors to absorb the frontier knowledge they lack and their analysis in the context of the Industry 4.0 this becomes of paramount importance.

3. Empirical application

3.1. Dataset and main variables

The empirical analysis makes use and combines three main sources of data: European Patent Office (EPO)'s PATSTAT, Financial Times's fDi Markets, and Moody's Zephyr. As we will explain in the following, the merge of these data sources led us to carry out our yearly analysis over the period 2004–2017. Furthermore, as we will also explain, the territorial unit of analysis at which we investigate the access to foreign knowledge for the development of I4.0 technologies is represented by metropolitan NUTS 3 regions.[2]

To start with, we extract from PATSTAT details on EU patent applications to the EPO and their backward citations. We focus on the EPO route, rather than using data on patent applications filed at national offices, because legal and administrative procedures tend to differ across the latter and statistics are not always comparable across countries (OECD 2009). Furthermore, the geographical focus of the study has led us prefer the EPO regional route to the international one (e.g. the Patent Co-operation Treaty procedure with the World Intellectual Property Organization, WIPO) because EU countries are more likely to file their application with the EPO than via the latter (OECD 2019).

We identify I4.0-related patents through a search query on titles and abstracts based on a list of keywords. The literature on I4.0 does not yet agree on a standard method for the identification of digital-related inventions. Recent contributions in this field have relied on hierarchical patent classification systems (e.g. International Patent Classification, IPC, or Cooperative Patent Classification, CPC) following the research initiated by the UK Intellectual Property (IP) Office (2013, 2014a; UK IP Office 2014b, 2014c) and further developed in subsequent studies (Ardito, D'Adda, and Messeni Petruzzelli 2018; Corradini, Santini, and Vecciolini 2021; Fujii and Managi 2018). Other scholars have adopted keyword inclusion/exclusion criteria applied to the text fields of patents or publications (Bianchini, Damioli, and Ghisetti 2023; Van Roy, Vertesy, and Damioli 2020; Webb, Bloom, and Lerner 2018), whereas a third stream of contributions have used a combination of both methods (WIPO 2019; Baruffaldi et al. 2020; EPO 2020; Martinelli, Mina, and Moggi 2021).[3]

In our work, we adopt a list of I4.0-related keywords, which we apply to the patent's abstract and title to select EU I4.0 invention.[4] We refrain from using information on the IPC technological classes, because current classifications are not detailed enough and they often return false negatives, failing to capture digital activities in certain fields, such as robotics, or return false positives, identifying certain patents as related to I4.0 technologies when in fact they are not. For instance, by adopting existing details on IPC classes it is not possible to distinguish big data-based inventions from those based on conventional data.[5]

[2]The metropolitan regions correspond to NUTS 3 regions or combinations of NUTS 3 regions constituting agglomerations of at least 250,000 inhabitants. These agglomerations were identified using the Eurostat and European Commission DG REGIO classification based on Urban Audit's Functional Urban Area (FUA). These are 'functional economic units' based on density and commuting patterns of the smallest administrative units for which national commuting data are available (NUTS 3 level in Europe). NUTS 3 regions with more than 50% of the population living within a given agglomeration are aggregated in a metropolitan region.

[3]Recently, supervised machine learning for large-scale classifications has also been adopted in identifying artificial intelligence patents Miric, Jia, and Huang (2023).

[4]Figure A1 in Appendix A shows the full list of keywords.

[5]Further details on the selection of I4.0-related patents are provided in Bello et al. (2023).

We derive our search criteria by building on a list of keywords developed by different sources: Bianchini, Damioli, and Ghisetti (2023), the taxonomy and dimensions of the digital technology ecosystem identified by the OECD (2019), as well as recent contributions on the patent mapping of AI (Baruffaldi et al. 2020) and of I4.0 technologies (Martinelli, Mina, and Moggi 2021). Accordingly, the keywords were selected to map the following categories of technologies: additive manufacturing, AI, big data, blockchain, computing infrastructures, IoT, and robotics. Bianchini, Damioli, and Ghisetti (2023) provides a thorough description of these categories.

3.1.1. Dependent variable

By relying on patent data and following a consolidated stream of research (Jaffe 2022), we use information on patents' *backward citations* to map knowledge flows. More precisely, we define the dependent variable, $Backcit_{i,j,t}$, as the count[6] of backward patent citations included in each of the I4.0-related patents of EU region i at year t and referring to the patents by inventors from country j. To do that, we georeference the citing patents at the metropolitan NUTS 3 region i based on the residence of the inventor. We adopt the fine-grained level of the metropolitan regions, because – unlike administrative geographical units – it allows for a spatially coherent representation of economic activities. The cited patents are instead georeferenced at the country level (j), as information on the region of residence of inventors cannot be consistently collected for cited patents filed at non-EPO patent offices.

While our analysis endorses a country-by-region, rather than region-by-region, perspective due to data constraints, it also rests on the assumption that national borders constitute a substantial discontinuity in the creation and diffusion of knowledge, consistent with recent research emphasising the crucial role of national innovation systems in global innovation networks (e.g. Fusillo et al. 2024). Thus, adopting a (cited) country-level perspective is valuable for comprehending the role of FDIs as a means for regions to access foreign knowledge from these countries. Still, as regional borders may also constitute discontinuities in knowledge diffusion, we perform some additional analysis at the level of cited regions. However, in this case we need to limit our analysis to the US and EU, for which we could obtain information on (cited) inventor location at a finer geographical level.

In constructing the dependent variable, we use inventors' residence rather than assignees' address, because the former more closely proxies the true location of knowledge development. Assignee locations – particularly for MNCs – are often selected for tax optimisation, legal infrastructure, or centralised IP management, and may not coincide with where the invention actually occurred (Almeida and Phene 2004; Griffith, Harrison, and Van Reenen 2006; Karkinsky and Riedel 2012). In contrast, inventor-level data offer finer spatial precision (Crescenzi, Gagliardi, and Iammarino 2015; Mancusi 2008a, 2008b), which is essential for accurately mapping regional and cross-border knowledge flows. Even in the context of I4.0 – where some innovations require specialised labs – many core activities (e.g. software coding, data analytics, AI algorithm design) occur in distributed R&D hubs or remote workspaces, making inventor residence a robust indicator of inventive location (Corradini, Santini, and Vecciolini 2021; Furman and Stern 2002; Niosi 2002).

It is worth noting that our data do not provide any information on whether local citing inventors are employed by an MNC and, in case, whether cited patents are within the same business group. This prevents us from considering the extent to which backward citations originate from foreign subsidiaries of MNCs in EU regions and, even more, whether these subsidiaries cite patents invented by their parent company. From a conceptual point of view, both the direct effect, due to the access to within-MNC knowledge sources, and the indirect effect, related to the extent to which this access to knowledge sources is extended to local firms, are relevant. Inventors at local subsidiaries are exposed to knowledge sources from the parent company and other subsidiaries within the MNC. These inventors can in turn leave the MNC and bring this knowledge with them in other local firms or can collaborate with other local inventors facilitating an indirect access to those sources of knowledge. A limitation of our study is that we can only measure the role of FDIs in the access to non-local knowledge sources, but we cannot distinguish the relative contribution of knowledge transfer occurring within the MNC's organisational boundaries from knowledge transfer to domestic firms. This is a recurrent problem in large-scale analyses of patent data and would require identifying the global corporate structures of all firms patenting in EU regions. In this respect, it must be noticed that studies that

[6]We use fractional counting of patents by region for those patents with inventors from multiple regions. The same applies for citations count where the inventors of the cited patent reside in different countries.

investigate intra-MNC knowledge transfer through backward citations typically focus on a limited number of firms, for which the global corporate structure can be identified and linked with patenting activities (e.g. Castellani, Lavoratori, et al. 2022). In the case of a large-scale study on all EU regions, like our own, identifying the global corporate structures of innovative firms would instead not be feasible.

3.1.2. Focal regressors and controls

The focal regressors refer to the *innovative FDIs* that region *i* receives from country *j* at a certain time *t*. To this purpose, we retrieve data about greenfield FDIs and cross-border M&As that MNCs carry out across regions from two different data sources. We have drawn data on greenfield FDIs directed to European regions from the Financial Times' fDi Markets. Following an established practice (Castellani and Pieri 2013, Belderbos et al. 2016; Damioli and Marin 2024), we define *innovative greenfield FDIs* as the investment projects MNCs make for establishing foreign activities in research and development (R&D) and design, development and testing (DDT) business functions. As for cross-border M&As, we used data from Moody's Zephyr to identify all cross-border M&As of target companies based in the EU (including the United Kingdom) entailing the acquisition of a significant degree of control of the target (at least 50% of its shares). Following the methodology used by Aquaro, Damioli, and Lengyel (2023) and Damioli and Marin (2024), we define *innovative cross-border M&As* as those in which the target held at least one patent, based on data from the Moody's Orbis IP database. This approach aligns with a growing body of research that uses patents to track innovative M&As under the premise that the presence of patents among the target firm's assets signal its technological strength (Aquaro, Damioli, and Lengyel 2023; Breitzman and Thomas 2002; Damioli and Marin 2024; Morton and Shapiro 2014; Park, Yoon, and Kim 2013). In order to align with the dyadic nature of the analysis, we georeference inward FDIs at the metropolitan NUTS 3 regional level, based on the city level information provided in fDi Markets and the address of the target company provided in Zephyr.

Using this information, we first count the number of innovative FDI projects, both greenfield FDIs and cross-border M&As, from cited country *j* to citing (EU) region *i* in year *t*. Due to the extreme skewness of the distribution of innovative FDIs (with over 98% of observations registering zero and only 0.2% recording more than one FDI project), we define the focal regressor, $InnovativeFDI_{i,j,t}$, as a binary indicator taking the value 1 when region *i* receives at least one innovative FDI from country *j* in year *t*, and 0 otherwise. This dichotomous specification allows us to capture the extensive margin of internationalisation – that is, whether or not a region establishes a knowledge-intensive FDI linkage with a given country – which is particularly relevant in the context of sparse FDI flows.[7] Conceptually, the presence of even a single innovative FDI can signal the opening of a potential knowledge pipeline, and is thus meaningful for tracing cross-border knowledge integration.

As detailed in the following section, the econometric model also includes a set of dyadic variables that capture both the manifold 'distances' between locations and other channels of knowledge transfer. Geographic distance captures the transportation and coordination costs that may inhibit the flow of codified knowledge, making inventors potentially less likely to cite patents from distant countries (Dachs and Pyka 2010; Picci 2010). Similarly, time-zone differences impede real-time communication and collaboration, potentially reducing the likelihood that regional inventors will draw on and cite foreign prior art (Marjit 2007). We further control for common currency, language, religion, and legal origin – factors shown to reduce transaction, cultural, and regulatory frictions that impede collaboration and information exchange across borders, and consequently increase the likelihood that regional inventors will draw on and cite foreign prior art (Eden and Miller 2004; Nielsen, Asmussen, and Weatherall 2017). We also include cross-country mobility of inventors, bilateral trade flows, and non-innovative FDIs as additional controls for other potential channels of knowledge diffusion that could confound the role of our focal variable (Andersson, Bjerke, and Karlsson 2013; Boschma, Martin, and Minondo 2016; Crescenzi, Gagliardi, and Iammarino 2015).

[7]To capture the intensive margin of internationalisation - the intensity with which a region links with a given country via FDI – we explored an alternative specification using a count variable (i.e. the number of innovative FDIs from a given country to a given region in a given year). While results – available from the authors upon request – are consistent with those obtained using the binary variable, the extreme sparsity of the data – more than 98% of observations with zero FDIs and only 0.2% with than one – led us to focus on the binary specification.

To build up distance variables, we used indicators provided in the CEPII database for time zones differences and common currency, religion, legal origin and spoken language, and manually computed region-by-country geographical distances. More precisely, region-by-country geographical distances were computed from the centroid of the region to the centroid of the country.

With respect to trade flows, we used the sum of bilateral (country-to-country) gross imports and exports from the OECD Trade in Value Added (TiVA) database. As for non-innovative FDIs, we included a measure of greenfield FDIs in manufacturing activities, which we constructed analogously to the focal independent variable from the fDi Markets database, and a measure of non-innovative M&As when target companies do not have any patent. With respect to cross-country mobility of inventors, we used two alternative measures. The first one exploits the number of foreign inventors by citizenship in each of the citing regions covered in the sample, from which we compute a five-year moving average in order to smooth volatility (especially for smaller regions).[8] This is an ideal control variable in our setting, as it allows to focus on the kind of migration flows that is most salient for local patent activities. However, cross-border mobility of inventors is available up to 2011 only (for further details see Miguelez and Fink 2017; Miguelez and Morrison 2022; Miguelez and Noumedem Temgoua 2020). This implies that we had to carry data forward after 2011, assuming that no change occurred in migrant inventors between 2012 and 2016. We therefore also adopted an alternative specification using country-to-country migration inflows taken from the OECD International Migration Database. This alternative measure has two key limitations: it does not have any variation across citing regions within the same country and it is imperfectly correlated with the cross-border transfer of knowledge embodied in migrant inventors.[9] Overall, given that data limitations make these variables imprecise for our analysis, and the fact that other dyadic variables in the model already pick-up the effect of the cross-border linkages at stake, we need to be cautious in interpreting the relative findings, and addressing this limitation should be high in the agenda of future research.

The above defined dyadic variables measuring FDIs, foreign inventors and trade flows, as well as the foreign backward citations made by I4.0 related patents, are time varying over the period on which we focus the analysis: 2004–2017. The choice of this period is dictated by the nature of patent data, collected for the period 2004–2017, and with respect to which FDI data have been lagged of one year (see the econometric strategy in Section 3.3), being thus available from 2003 until 2016. In particular, we need to allow a sufficient time lag between the filing date and the time at which patents were observed in the PATSTAT database when we retrieved I4.0-related patents. Basic descriptive statistics for the dependent and independent variables are provided in Table 1.

Table 1. Descriptive statistics on main variables.

	Mean	Sd	Min	Max
Backward citations of IV.0-related patents	0.21	1.49	0.00	115.32
Inward innovative FDI	0.03	0.18	0.00	1.00
Inward innovative greenfield FDI	0.02	0.12	0.00	1.00
Inward innovative cross-border M&A	0.02	0.14	0.00	1.00
Inward non-innovative FDI	0.07	0.26	0.00	1.00
Inward manufacturing greenfield FDI	0.02	0.13	0.00	1.00
Inward non-innovative cross-border M&A	0.06	0.24	0.00	1.00
Time-zone difference	2.96	3.31	0.00	11.88
Common currency	0.24	0.43	0.00	1.00
Common religion	0.22	0.23	0.00	0.97
Common legal origin	0.19	0.39	0.00	1.00
Common language	0.10	0.30	0.00	1.00
Geographic distance (in log)	7.80	1.13	3.22	9.90
Inflows of foreign inventors (in log)	0.07	0.66	−1.61	6.60
Trade flows (in log)	7.71	3.99	0.00	12.32

Notes: the statistics are computed over the 67,742 (citing region-cited country-year) observations composing the estimation sample of the model with the inward innovative FDI regressor introduced at one lag. Backward citations are computed using a fractional counting approach. Inflows of foreign inventors are 5-years moving averages. Trade flows are measured at the country-to-country level.

[8]We are very grateful to Ernest Miguelez for sharing the data on migrant inventors with us.

[9]As the results of the analysis turned out to be unaffected by the choice of the variable used to measure migration flows, we report results of models using the inflows of migrant inventors only. Results of models using the country-to-country migration inflows are available upon request.

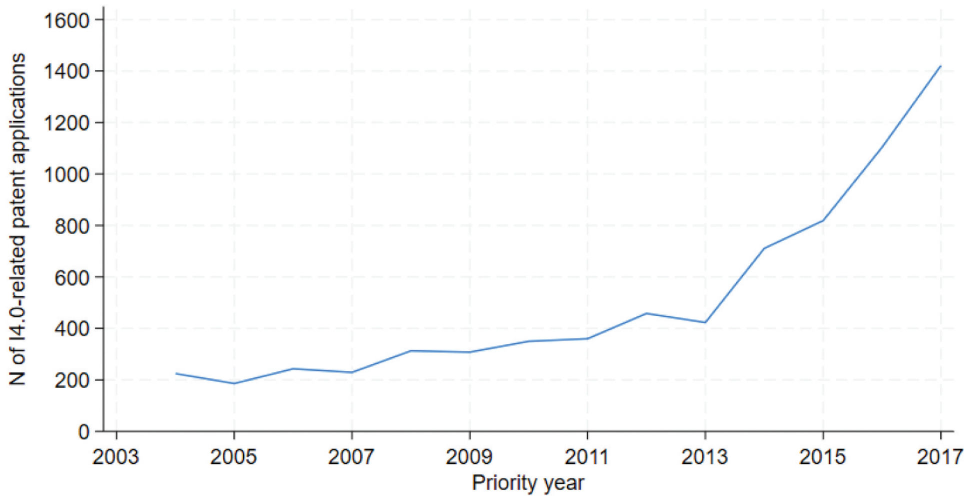

Figure 1. I4.0-related EU patent applications, 2004–2017. Notes: Patent applications to the European Patent Office with one or more inventors residing in EU27 Member States or the United Kingdom.

3.2. Descriptive statistics

Our approach delivered a sample of 7,148 EU I4.0-related patents in the 2004–2017 period, each of them citing 1.9 other patents on average. Figure 1 shows that the number of EU patent applications in I4.0 technologies has significantly increased in the most recent years, reflecting an unprecedented widespread application to a growing number of industries and business functions (Clark 2015; McKinsey 2017). As Figure 2 shows, the development of these technologies is quite scattered across a relatively small number of EU NUTS3 regions, with a certain concentration in key innovation hubs like Stuttgart and Munich in Germany, Paris (Île-de-France) in France, London in the UK, Stockholm, Gothenburg and Skåne in Sweden, Helsinki in Finland, Barcelona in Spain and Turin in Italy.

EU I4.0-related patents do rely on foreign knowledge sourced especially outside the EU. Foreign backward citations of I4.0-related patents also showed a marked increase in recent years (Figure 3) and, to a large extent, they cite patents with inventors residing in non-EU countries (Figure 4). Indeed, extra-EU patent citations account for nearly 60% of all patent citations found in EU I4.0-related patents, with the United States and Japan accounting for the largest shares. Within the EU, Germany and France are the most important source of knowledge for digital technologies.

As for FDIs, our sample includes 1,362 inward innovative greenfield FDIs directed to the EU and 1,652 cross-border M&As of EU targets, whose flows have grown substantially in the EU over our period of analysis (Figure A2 in Appendix A), with a blip due to the financial crisis of 2008. In line with previous evidence (e.g. Castellani and Pieri 2016; Crozet, Mayer, and Mucchielli 2004), inward innovative FDIs are quite scattered across locations, with few metropolitan NUTS3 regions absorbing remarkable number of projects (over 500) in the retained period (Figure 5). In terms of origin countries of innovative FDIs, inward FDIs originate mainly from the US and EU countries (Figure 6).

3.3. Econometric strategy

We estimate a distributed-lag gravity model wherein the number of dyadic citations between an EU citing region i and a cited foreign country j (within or outside the EU), $Backcit_{i,j}$, depends on the occurrence of dyadic innovative FDI flows from the latter to the former, $InnoFDI_{i,j}$, and a number of additional potential explanatory factors. Our baseline equation is as follows:

$$Backcit_{i,j,t} = \alpha + \sum_{s=1}^{N} \beta_s \, InnoFDI_{i,j,t-s} + D'_{i,j,t-1}\,\beta_5 + \gamma_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t} \quad N = 4 \tag{1}$$

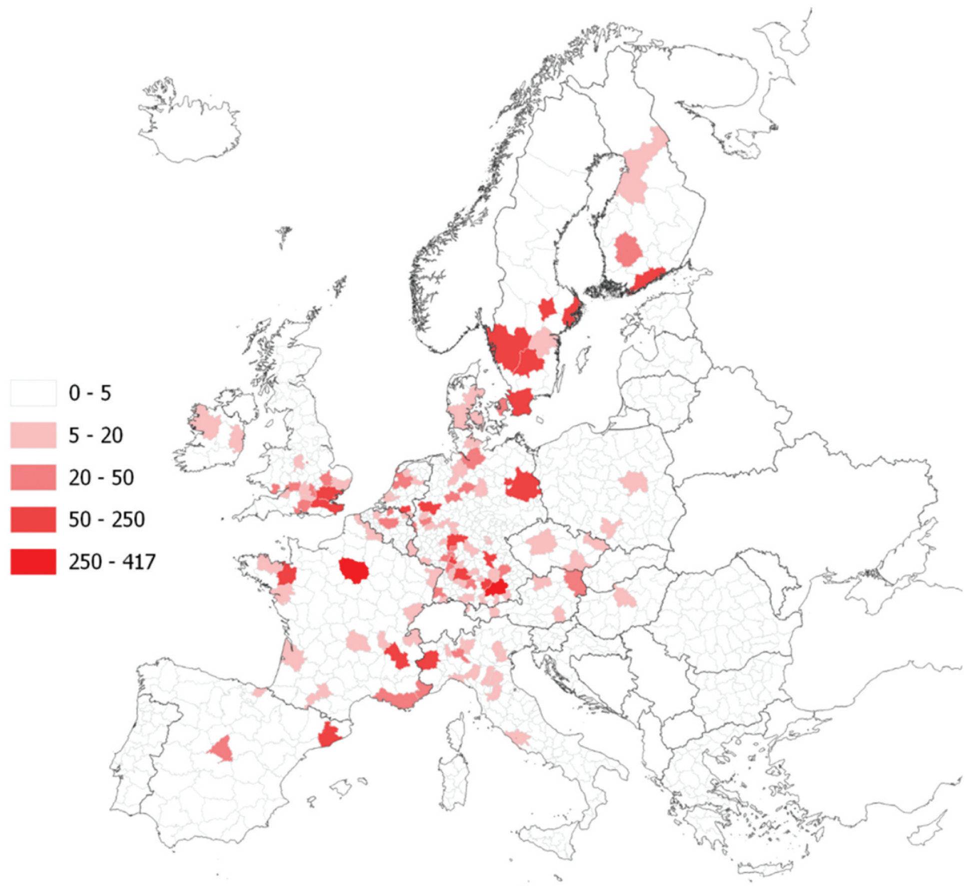

Figure 2. Geographical distribution of I4.0-related EU patent applications, 2004–2017. Notes: Patent applications to the European Patent Office with one or more inventors residing in EU27 Member States or the United Kingdom. Fractional counting is used to attribute patent regions.

$D'_{i,j,t-1}$ is a vector of dyadic variables that includes the geographic, cultural, and alternative knowledge-channel controls defined in Section 3.1[10] $\gamma_{i,t}$ and $\delta_{j,t}$ are year-specific citing-region and year-specific cited-country fixed effects, respectively, which capture location-specific time-varying unobserved shocks (and subsume year, citing-region and cited-country fixed effects).[11]

To capture the dynamic association between InnoFDI and backward citations, we specify a distributed-lag model that allows some delay in the effect. Due to data constraints, we estimate our focal regressors at one, two, three and four lags ($N = 4$).

We estimate the model by means of the Pseudo-Poisson Maximum Likelihood (PPML) estimator. The full set of estimates for our baseline model (Table 2) is provided in Table A1 of Appendix A, while Tables 2-6 report the coefficients of the focal regressors.[12]

[10]To simplify notation, we include only one vector of controls denoted to vary across *i*, *j* and t. However, it is worth mentioning that some of the variables in the vector *D* vary across citing regions *i* and cited countries *j*, with no time variation (including time-zone difference, common currency, common religion, common legal origin, common language, geographic distance), others vary across citing countries, cited countries and time (trade flows) and only the inflows of foreign inventors and the occurrence of non-innovative FDI flows varies across citing regions, cited country and time.

[11]While dyad (region – country) fixed effects are commonly used in gravity-style PPML estimations to account for time-invariant bilateral unobservable characteristics, we chose not to include them due to the extreme sparsity of our data. Over 98% of region – country – year cells in our sample record zero innovative FDIs, and most citation counts are also zero. In this context, introducing high-dimensional dyad fixed effects absorbs nearly all the variation in both the dependent and focal variables, leading to numerical instability and implausible estimates. Our specification, which includes region – year and country – year fixed effects, strikes a better balance by controlling for unobserved time-varying shocks while preserving sufficient within-dyad variation to estimate the relationships of interest.

[12]The full set of estimates related to Tables 3– 6 is available from the authors upon request.

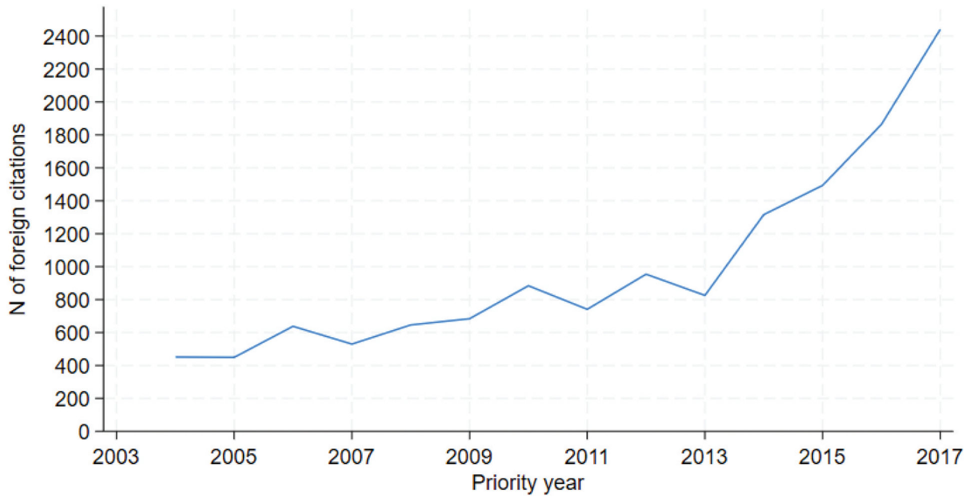

Figure 3. Foreign backward citations of I4.0-related EU patent applications, 2004–2017. Notes: foreign backward citations of patent applications to the European Patent Office with one or more inventors residing in EU27 Member States or the United Kingdom.

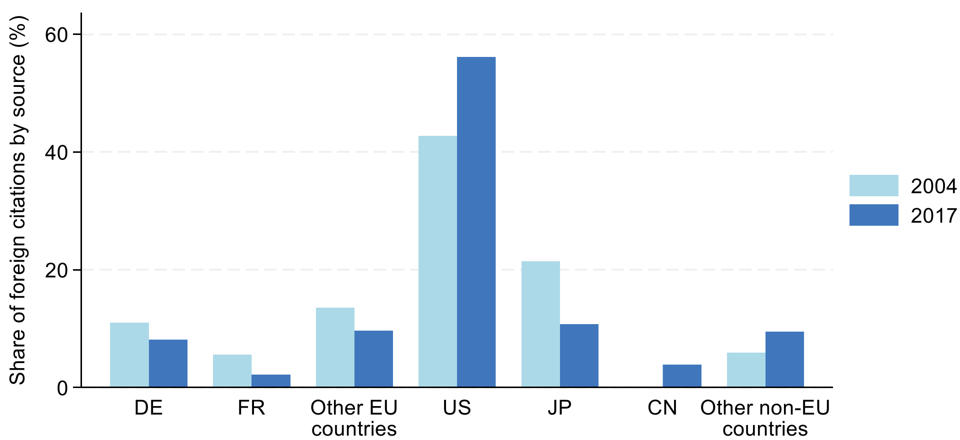

Figure 4. Foreign backward citations of I4.0-related EU patent applications by cited country, 2004–2017. Notes: foreign backward citations of patent applications to the European Patent Office with one or more inventors residing in EU27 Member States or the United Kingdom.

4. Results

4.1. Baseline specification

Table 2 reports the results of the baseline model in Eq. (1) for different values of the time lags (1, 2, 3 and 4) across the columns. The estimates show that inward innovative FDIs are significantly and positively associated with backward foreign citations in I4.0 (EPO) patents made by EU-based inventors. These results are consistent with our main research hypothesis about a positive association between inward-FDIs and regions' use of foreign knowledge as prior art for the development of I4.0 technologies.

For what concerns our control variables (Table A1), the estimates support the expectation that the number of citations in I4.0-related patents is negatively correlated with the geographical distance and the time-zone difference between citing and cited locations, and positively correlated with the common legal origin. These results support the idea that, even though knowledge is intangible, physical and institutional proximity still matter for the exchange of knowledge (Boschma 2005; Castellani, Jimenez, and Zanfei 2013; Dachs and Pyka 2010; Picci 2010). Non-innovative FDIs are positively correlated with cross-border citations, but the magnitude of the effect is smaller than for innovative FDIs. Furthermore, this finding is

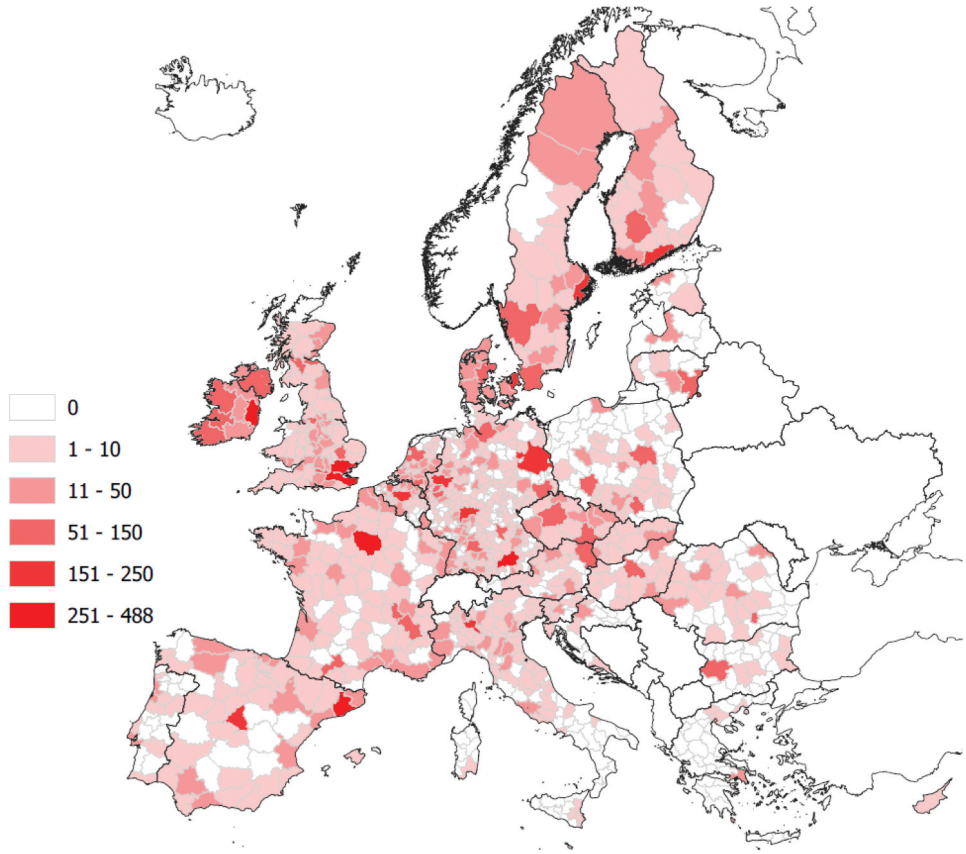

Figure 5. Regional distribution of inward innovative FDIs, 2003–2016. Notes: inward innovative FDI projects to the EU27 Member States and the United Kingdom.

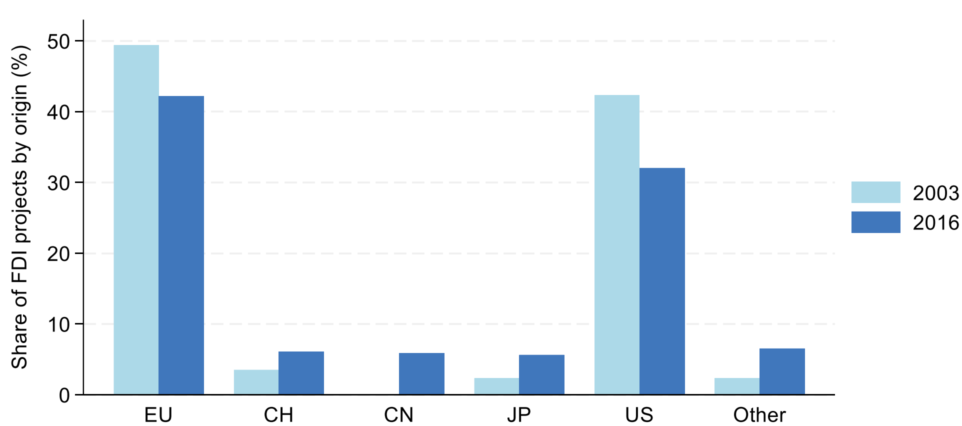

Figure 6. Inward innovative FDIs to the EU, by origin, 2003–2016. Notes: inward innovative FDI projects to the EU27 Member States and the United Kingdom.

not robust to some of the extension of the empirical analysis discussion below.[13] Migration (inflows of foreign inventors) and international trade are surprisingly not correlated with cross-border citations. This may be related to the fact that other dyadic variables in the model already pick-up the effect of such cross-border linkages, or it could reflect some measurement error. In fact, while FDIs vary across citing regions and cited countries, trade lacks regional variability. For cross-border migration of inventors we face the lack of variation over time after 2011. Given the importance of these alternative channels for knowledge transfer,

[13]Results available upon request.

Table 2. Foreign backward citations of IV.0-related patents and inward innovative FDIs.

Dependent variable: number of backward citations	(1)	(2)	(3)	(4)
Inward innovative FDI (lag 1)	0.123***	0.103***	0.086**	0.068*
	(0.036)	(0.037)	(0.043)	(0.040)
Inward innovative FDI (lag 2)		0.115**	0.096**	0.103**
		(0.045)	(0.041)	(0.041)
Inward innovative FDI (lag 3)			0.089**	0.074
			(0.044)	(0.048)
Inward innovative FDI (lag 4)				0.102**
				(0.052)
Inward innovative FDI (cumulative effect)	0.123***	0.218***	0.270***	0.348***
	(0.036)	(0.057)	(0.066)	(0.099)
Pseudo-R2	0.686	0.690	0.693	0.695
Number of citing regions	615	609	602	595
Number of cited countries	66	66	65	65
Observations	67,742	65,766	63,486	61,159

Notes: PPML regression estimation. All models control for time-zone difference, common currency, common religion, common legal origin, common language, geographic distance (in log), inflows of foreign inventors (in log), trade flows (measured at the country level), inward non-innovative FDIs, citing region-year and cited country-year fixed effects. Standard errors clustered by citing region-cited country pairs are reported in parentheses. Full models estimates are reported in Table A1 in Appendix A. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

we need to be cautious in interpreting our findings, and addressing this limitation should be high in the agenda of future research.

4.2. Does the origin of FDIs matter?

We next delve into the influence of knowledge generated in diverse locations on the advancement of I4.0 technologies in the EU. For this purpose, we differentiate between innovative FDIs originating within the EU and those originating from countries outside the EU. This differentiation becomes particularly pertinent given the EU's comparative lag in developing I4.0 technologies in comparison to leading countries such as the United States and advanced Asian nations (Brattberg, Csernatoni, and Rugova 2020; Guarascio and Stöllinger 2025; Van Roy, Vertesy, and Damioli 2020). In this context, inward FDI could serve as a significant channel for accessing knowledge originating outside the EU, with FDI from non-EU countries potentially playing a more substantial role in the focal relationship addressed in this study.

To test this potential difference, we estimate a fully interacted variation of Eq. (1), where each of the model covariates is interacted with a dummy variable referring to EU regions and is added to the equation. Table 3 reports the regression results of this extended model. The estimates show that the positive relationship between inward innovative FDIs and foreign backward citations in I4.0-related patents is driven by investments from outside the EU. This is consistent with our previous descriptive evidence showing that EU inventors use more extra-EU than EU knowledge in their I4.0 inventing activities. And this is in turn accountable by the fact that the EU is lagging behind other advanced countries, such as the US, in developing I4.0 technologies. Still consistently with that, EU regions could benefit from important catching-up opportunities when MNCs from countries outside the EU engage in innovative FDI projects in their locations. In additional analyses, available by the authors upon request, we have restricted the sample to

Table 3. Foreign backward citations of IV.0-related patents and inward innovative FDIs, by FDI origin.

Dependent variable: number of backward citations	Lag 1	Lag 2	Lag 3	Lag 4
Inward innovative FDI, extra-EU origin (cumulative effect)	0.113**	0.170**	0.216**	0.229**
	(0.049)	(0.068)	(0.088)	(0.103)
Inward innovative FDI, EU origin (cumulative effect)	−0.144	−0.112	−0.196	−0.128
	(0.089)	(0.137)	(0.173)	(0.190)
Pseudo R2	0.688	0.691	0.695	0.697
Number of citing regions	615	609	602	595
Number of cited countries	66	66	65	65
Observations	67,701	65,725	63,445	61,118

Notes: PPML regression estimation. All models control for time-zone difference, common currency, common religion, common legal origin, common language, geographic distance (in log), inflows of foreign inventors (in log), trade flows (measured at the country level), inward non-innovative FDIs, citing region-year and cited country-year fixed effects. Standard errors clustered by citing region-cited country pairs are reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

three largest countries of origin in terms of citations from EU I4.0 patents (US, Japan and Germany) but we have not found any clear evidence that our findings are driven by any of these three countries.

4.3. Does the type of FDIs matter?

Previous studies indicate that the mode of entry can influence the impact of FDI inflows on host locations. Conceptually, cross-border M&As may facilitate stronger knowledge transfer in the short term compared to greenfield investments, due to the target company's role in quickly integrating the acquiring MNC into the local economy (Hitt et al. 1996). In contrast, establishing knowledge interactions with local actors is a slower, costlier, and more uncertain process for MNCs entering through greenfield investments (Blomkvist, Kappen, and Zander 2019; Mudambi 1998). Additionally, greenfield FDIs can disrupt local labour markets by competing for local scientific and technical talent to staff new innovative activities (Barkema and Vermeulen 1998), whereas MNCs acquiring innovative local firms are more likely to utilise the existing workforce, leading to a less disruptive impact (Cantwell and Mudambi 2005). Empirical studies support these claims. For example, Ashraf, Herzer, and Nunnenkamp (2016) find that M&As increase total factor productivity in developed countries, while greenfield FDIs have no effect. Similarly, Damioli and Marin (2024) show that cross-border M&As have a more positive effect than greenfield FDIs on patenting activity in EU destination regions.

Still, if one focuses on intra-MNE knowledge transfer, the literature has highlighted that many M&As target firms are acquired because of the specific assets they possess, or they have access to, and this may justify a lower knowledge transfer from HQ to subsidiary (Arnold and Javorcik 2009). Conversely, in the case of greenfield FDI, HQ need to transfer some of their firm-specific assets to the foreign subsidiary, in order to allow overcoming the liability of foreignness (Narula et al. 2019, Zaheer 1995).

It is therefore valuable to explore whether and to what extent our findings vary based on the entry mode chosen by the investing MNC. To investigate this potential difference, we estimate a modified version of Eq (1), distinguishing between innovative greenfield FDIs and cross-border M&As. Table 4 presents the regression results from this extended model. The findings indicate that the positive relationship between inward innovative FDIs and foreign backward citations in I4.0-related patents holds for both greenfield FDIs and cross-border M&As.

Table 4. Foreign backward citations of IV.0-related patents and inward innovative FDIs, by FDI mode.

Dependent variable: number of backward citations	(1)	(2)	(3)	(4)
Inward innovative greenfield FDI (lag 1)	0.122***	0.091**	0.080*	0.078
	(0.041)	(0.043)	(0.047)	(0.048)
Inward innovative greenfield FDI (lag 2)		0.004	−0.036	−0.061
		(0.060)	(0.059)	(0.064)
Inward innovative greenfield FDI (lag 3)			0.097	0.088
			(0.070)	(0.065)
Inward innovative greenfield FDI (lag 4)				0.120*
				(0.068)
Inward innovative cross-border M&A (lag 1)	0.126***	0.114**	0.086*	0.077*
	(0.048)	(0.047)	(0.048)	(0.046)
Inward innovative cross-border M&A (lag 2)		0.157***	0.139***	0.145***
		(0.041)	(0.041)	(0.041)
Inward innovative cross-border M&A (lag 3)			0.015	0.001
			(0.047)	(0.046)
Inward innovative cross-border M&A (lag 4)				0.023
				(0.055)
Inward innovative greenfield FDI (cumulative effect)	0.122***	0.095	0.141	0.224*
	(0.041)	(0.077)	(0.088)	(0.117)
Inward innovative cross-border M&A (cumulative effect)	0.126***	0.271***	0.240***	0.246**
	(0.048)	(0.064)	(0.081)	(0.107)
Pseudo R2	0.687	0.690	0.693	0.695
Number of citing regions	615	609	602	595
Number of cited countries	66	66	65	65
Observations	67,742	65,766	63,486	61,159

Notes: PPML regression estimation. All models control for time-zone difference, common currency, common religion, common legal origin, common language, geographic distance (in log), inflows of foreign inventors (in log), trade flows (measured at the country level), inward manufacturing greenfield FDI, non-innovative cross-border M&A, citing region-year and cited country-year fixed effects. Standard errors clustered by citing region-cited country pairs are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4.4. Does the type of I4.0 technology matter?

Recent research on I4.0 technologies highlights that different technologies within this realm vary in their application domains and characteristics, particularly in their role as enabling versus general-purpose technologies (as discussed in Martinelli, Mina, and Moggi 2021). For example, Goldfarb, Taska, and Teodoridis (2023) show that AI and big data consistently rank highly across several indicators matching the three GPT criteria: widespread use, potential for innovation, and innovation in application industries (Bresnahan and Trajtenberg 1995). Robotics and cloud computing also perform well across indicators, whereas technologies like additive manufacturing, blockchain, and IoT rank much lower.

Although we do not have a strong prior assumption about how easily knowledge related to specific Industry 4.0 technologies might be transferred across borders through FDIs, testing for a potentially differentiated effect for these technologies could offer valuable insights. To explore this, we created separate dependent variables for different groups of I4.0 technologies and conducted regressions using the baseline model specification. Specifically, we classified I4.0 technologies into three groups: AI and big data, robotics, and other technologies. These groupings were based on the degree of technological integration and complementarity (e.g. grouping AI and big data patents together) and their prevalence in the sample of citing patents in terms of shares of the total (25.5% AI and big data, 43.7% robotics, 30.8% other technologies).

Table 5 shows that the cumulative effects at time lag 4 of innovative inward FDIs are not statistically different from zero across all technology groups, due to very large standard errors. While the point estimate for AI and big data is larger than that for other I4.0 technologies, they are all quite imprecisely estimated. Indeed, when we consider the different I4.0 sub-technologies, due to the increased number of origin and destination locations with no citations, the number of citing regions and the number of observations drops dramatically. In these cases, region-year pairs without any patents and country-year pairs receiving zero citations are perfectly explained by region-year and country-year effects. All in all, considering the data limitation we would not draw any strong conclusion from this sub-technology analysis.

4.5. Region-to-region analysis

As we have anticipated, the results of the previous analysis, at the country-by-region level, are based on the premise that national borders create a substantial discontinuity in the generation and dissemination of innovative knowledge. This aligns with recent findings on global innovation networks, underscoring the importance of national innovation systems in the shaping of innovation development and diffusion (see, for instance, Fusillo et al. 2024). Consequently, adopting a country-level perspective proves insightful in understanding the function of inward FDIs as a mechanism for regions accessing foreign knowledge.

Yet, our choice of referring to pairs of citing regions and cited countries as units of analysis is also dictated by the limited information on sub-national locations of cited inventors available from our data sources. Indeed, technological knowledge transfer has also a supply-side geography, with spatially heterogeneous opportunities within the country to which a focal MNC refers, e.g. across its regions. Accordingly, a gravity model referring to pairs of citing regions and cited regions would enable us to better capture the heterogeneity across regions within cited countries, and this could make a difference especially in large countries.

Table 5. Foreign backward citations of IV.0-related patents and inward innovative FDIs, by I4.0 class.

Dependent variable: number of backward citations	AI and big data-related patents	Robotics-related	Other I4.0-related patents
Inward innovative FDI (cumulative effect, 4 lags)	0.315	−0.053	−0.165
	(0.258)	(0.135)	(0.253)
Pseudo-R2	0.760	0.672	0.722
Number of citing regions	290	436	330
Number of citing countries	28	26	32
Observations	7,897	16,426	10,798

Notes: PPML regression estimation. All models control for time-zone difference, common currency, common religion, common legal origin, common language, geographic distance (in log), inflows of foreign inventors (in log), trade flows (measured at the country level), inward non-innovative FDIs, citing region-year and cited country-year fixed effects. Standard errors clustered by citing region-cited country pairs are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Unfortunately, georeferencing citations at a fine geographical level is possible for a relatively small subset of cited patents. Yet, a good coverage is available for the EU and the US. While it is unfortunate that we cannot include regional heterogeneity for other countries, the EU and the US together account for 72% of I4.0 patents cited by inventors in EU regions. In addition, the US is a large and heterogeneous country in terms of knowledge creating activities and the source of the vast majority of non-EU citations. We therefore replicated the empirical analysis at the citing-region/cited-region level, by limiting cited patents' locations to EU and US regions.

To perform this region-by-region analysis, we have limited the count of cited patents to those filed at the EPO and at the United States Patent and Trademark Office (USPTO), or under the Patent Cooperation Treaty (PCT).[14] In so doing we have been able to assign cited patents to metropolitan NUTS 3 regions in the EU (therefore recreating the same geographical level adopted for the locations of the citing patents), and to US States. Due to the limited geographical coverage of cited patents, citations of I4.0 related patents is reduced by over 68% with respect to the baseline analysis at the citing-region/cited-country pair level. As for FDIs, exploiting the information on the city of where the investor/acquiror is located for each of the cross-border greenfield investments and M&A available in fDi Markets and Zephyr, respectively, we can count the number of innovative and non-innovative greenfield FDI for each citing EU region and cited US state pair over time. As for the main analysis, we then transform these counts into dummy variables. We can also compute the geographic distance from the centroid of each US state and each EU region and control for US State-year and EU region-year dummies. Unfortunately, other control variables (such as common currency, common religion, common legal origin, common language, inflows of foreign inventors, international trade) are only available for the US as whole, thus leading to potentially imprecise estimates.

Results reported in Table 6 confirm the findings of the baseline analysis. Region-by-region FDIs are associated with the correspondent region-by-region I4.0 patent citations with a positive cumulative effect. If anything, the finer geographical disaggregation allows us to get a more precise estimation of our main effects. Due to the smaller unit of analysis, the number of citations is also reduced, thus the scale of the dependent variable changes relative to the baseline country-to-region estimations. This suggests caution in interpreting the different magnitude of the coefficients in the region-to-region analysis relative to the baseline.

Table 6. Foreign backward citations of IV.0-related patents and inward innovative FDIs, region-to-region specification.

Dependent variable: number of backward citations of US and EU patents	(1)	(2)	(3)	(4)
Inward innovative FDI (lag 1)	0.836***	0.596***	0.452***	0.291*
	(0.186)	(0.166)	(0.166)	(0.162)
Inward innovative FDI (lag 2)		0.667***	0.553***	0.456***
		(0.156)	(0.140)	(0.140)
Inward innovative FDI (lag 3)			0.625***	0.496***
			(0.134)	(0.125)
Inward innovative FDI (lag 4)				0.529***
				(0.104)
Inward innovative FDI (cumulative effect)	0.836***	1.263***	1.630***	1.772***
	(0.186)	(0.289)	(0.350)	(0.359)
Pseudo R2	0.309	0.312	0.318	0.322
Number of citing regions	471	465	460	451
Number of cited countries	23	23	22	22
Observations	185,576	180,530	173,670	166,344

Notes: PPML regression estimation. All models control for time-zone difference, common currency, common religion, common legal origin, common language, geographic distance (in log), inflows of foreign inventors (in log), trade flows (measured at the country level),inward greenfield non-innovative FDIs, citing region- and cited region-year fixed effects. Standard errors clustered by citing-cited region pairs are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

[14]We used information available in the OECD REGPAT database to geolocate at the NUTS 3 level EU and US inventors of PCT and EPO cited patents. We then complemented this information with the State of US inventors in USPTO cited patents using the PATSTAT database. Georeferencing the excluded citations would have required the uncertain process of using the string of inventors' address provided by PATSTAT, which is beyond the scope of this study.

5. Conclusions and policy implications

Several policy initiatives in Europe and beyond are pushing for the design of new patterns of development to cope with major shocks and challenges the humankind must deal with nowadays. The development of new digital technologies, such as those at the core of the I4.0 paradigm, and the spread of their adoption across different domains, is at the core of these efforts, which could enable to combine the competitiveness advantages of the 'fabric of the future' with the requisites of a sustainable and inclusive development. However, the geography of this last wave of digital technologies reveals an unequal distribution across EU (and non-EU) regions and motivate an investigation into the factors that could facilitate their development in different territories. Given that the development of new local technologies – whether related to Industry 4.0 or more general innovations – depends on the novel combination of knowledge inputs that support patentable inventions, it is essential to examine the sources of prior-art knowledge that regional inventors rely on, as often indicated through patent citations. Therefore, focusing on the geographical distribution of prior-art knowledge for the development of I4.0 technologies, and the mechanisms that enable local inventors to access and cite this knowledge, becomes a critical issue to address.

The extant literature has mainly focused on the internal knowledge (and non-knowledge) related drivers of regional I4.0 technologies, paying only limited attention to the role that, in a scenario of globally integrated value chains and innovation networks, is played by external relationships through which regions could draw knowledge and competencies they might lack internally. In contributing to fill this gap, in this study we have focused on the role of inward FDIs. By combining the geography of innovation literature with international business studies, we argue that, by shaping knowledge linkages between places, FDIs constitute a leverage through which local economies can source internationally the knowledge required to develop, adopt and combine I4.0-related technologies.

To test this conjecture, we have relied on a gravity-modelling framework and, using a novel dataset over the years 2004–2017, we have investigated whether the knowledge base of I4.0 technologies developed in EU metropolitan NUTS 3 regions, as revealed by the backward citations of their I4.0-related patents, correlate with inward innovative FDIs into the regions. We did find that this relation is positive and statistically significant even by controlling for multiple confounding factors. In particular, we provide evidence that the number of backward citations in I4.0 patents registered in an EU region to patents by inventors located in a foreign country is positively correlated to the existence of some innovative FDIs in the EU by MNEs based in the said foreign country. This is a first important research result, which contributes to the still thin stream of research about the determinants of external (international) sources of knowledge for the development of new technologies like I4.0 ones. Our findings are consistent with the idea that innovative FDIs act as a conduit for cross-border knowledge spillovers by expanding access to non-local sources of knowledge. In other words, innovative FDIs increase the amount of prior knowledge that spill on local inventions, and in a way that mirrors the geography of FDIs. We have found this at work with respect to I4.0 technologies, but by identifying a mechanism that could apply to other technological domains too, on which future research could focus.

The second result that we have obtained is that the association between inward regional FDIs and foreign backward citations of I4.0-related patents is driven by innovative investments originating outside the EU, with respect to which the EU notably reveals a digital gap. This result suggests that FDIs could be a more powerful conduit of external knowledge for enabling regions to catch-up, rather than compete or forge-ahead in technological terms. With regard to the digital technologies of the I4.0 era, inward FDIs in innovative activities could serve as a vehicle for EU regions to catch up with countries at the frontier of I4.0 technologies.

Third, the findings indicate that both innovative greenfield FDIs and cross-border M&As are positively correlated with foreign backward citations in I4.0-related patents. While considerations about the preservation of domestic control on strategic assets may prevail in justifying discretionary policy interventions to favour greenfield FDIs over cross-border M&As, our findings indicate that the acquisition of innovative local assets by foreign MNCs is positively related to the access to non-local sources of knowledge used to develop I4.0 technologies in the EU.

From a policy perspective, these findings provide valuable new evidence on the role of innovative FDIs for the achievement of the objectives of the new European Industrial Strategy and the

European Digital Agenda. Indeed, the results indicate that attracting innovative FDIs can serve as a policy lever through which relevant knowledge for the development of I4.0 technologies can become more accessible to local inventors. Being reached by innovative FDI projects makes a regional ecosystem more exposed to foreign knowledge relevant for its inventions in the I4.0 domain. Accordingly, providing MNCs with incentives and favourable conditions for the development of innovative projects in a region reveals a channel to make its ecosystem more dynamic in accessing key sources of knowledge to develop new I4.0 technologies.

Another important policy implication descends from the fact that FDIs apparently serve to conduit I4.0 relevant knowledge that has been developed in the MNCs' home countries. This provides policy makers with an important 'radar' with which possibly select the MNCs that could contribute the most to the local development of I4.0 technologies, being based in countries at the frontier of the same technologies.

While innovative FDIs are thus relevant to feed the development of local I4.0 technologies, their attraction should be retained with scrutiny by EU policy makers. Inward innovative FDIs could in fact pose issues of technological vulnerability due to foreign dependency, which could affect the strategic autonomy the EU is struggling to gain.

In conclusion, it should be emphasised that, while the primary focus of the study is on Europe, the findings of the analysis may have broader implications beyond Europe. In particular, our study provides novel empirical evidence on an issue of general interest as it emerges, for example, in the 2030 Agenda for Sustainable Development (UN General Assembly 2015) – a 'Roadmap for redefining sustainable development as a people and planet agenda: A prosperous and fair world within the planetary boundaries' (2019, 7).

Of course, this study is not free from limitations, which future research should address to enhance the validity and broader implications of our findings. First, while our analysis uncovers robust associations between innovative inward FDIs and cross-border knowledge transfer in regional I4.0 technologies, it does not establish causality. Endogeneity concerns remain – for instance, due to the possible omission of variables at the dyadic level (i.e. between citing regions and cited countries).

Second, as we have anticipated, data constraints forced us to investigate our research issue using an asymmetric gravity model, in which dyads are represented by cited country and citing region. The use of a gravity model at the regional level would allow us to obtain more granular results, which would enable us to account for the within-country heterogeneity in the cited location and in the corresponding flows of FDIs. This approach would allow to control for cited region-specific factors, that could affect the propensity to engage in FDI and to be cited by other regions. This extension would require georeferencing patents on a very large scale, which is a non-trivial task. The robustness test on the subset of cited regions in the EU and US provides some reassurance, as it shows that the baseline results are more precisely estimated when a more granular geographical scale of cited regions is considered.

Another limitation pertains to the identification of alternative channels of knowledge transfer across borders, such as international trade and high-skilled migration. Our findings do not indicate significant effects of these mechanisms on cross-border citations of I4.0 technologies. However, this could be related to the imprecise measurement of international trade, which is not available at the regional level, and of migration of inventors, which is only available for a subset of the period of analysis.

Finally, our study cannot shed light on the mechanisms through which FDIs facilitate cross-border knowledge transfer. In particular, the nature of our data does not allow to identify whether a citing patent is filed by an affiliate of the investing MNC and whether citations refer to patents within the same multinational group. This issue recurs frequently when conducting extensive analyses of patent data on a large scale, necessitating the identification of the global corporate structures of all companies patenting within the EU. While both knowledge transfer within MNCs and between the MNCs and local firms enhance the local knowledge base needed for the development of I4.0 technologies, distinguishing the two mechanisms would offer further insights into the mechanisms of knowledge diffusion examined in this study. Accordingly, future research should investigate this issue by searching for and assembling more granular data about intra-firm and inter-firm citation patterns at the regional level, may be at the cost of a more focussed approach on a smaller set of regions or firms.

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Appendices

Appendix A: Additional tables and charts

Table A1. Foreign backward citations of I4.0-related patents and inward innovative FDIs, full regression results.

Dependent variable: number of backward citations	(1)	(2)	(3)	(4)
Inward innovative FDI (lag 1)	0.123***	0.103***	0.086**	0.068*
	(0.036)	(0.037)	(0.043)	(0.040)
Inward innovative FDI (lag 2)		0.115**	0.096**	0.103**
		(0.045)	(0.041)	(0.041)
Inward innovative FDI (lag 3)			0.089**	0.074
			(0.044)	(0.048)
Inward innovative FDI (lag 4)				0.102**
				(0.052)
Inward innovative FDI (cumulative effect)	0.123***	0.218***	0.270***	0.348***
	(0.036)	(0.057)	(0.066)	(0.099)
Time-zone difference	−0.082	−0.104**	−0.100*	−0.087
	(0.054)	(0.051)	(0.052)	(0.053)
Common currency	−0.038	−0.039	−0.051	−0.046
	(0.096)	(0.095)	(0.100)	(0.108)
Common religion	−0.133	−0.143	−0.151	−0.180
	(0.088)	(0.103)	(0.098)	(0.111)
Common legal origin	0.137**	0.140**	0.139**	0.161**
	(0.064)	(0.060)	(0.059)	(0.067)
Common language	0.091	0.079	0.071	0.040
	(0.098)	(0.097)	(0.093)	(0.087)
Distance (in log)	−0.167***	−0.167***	−0.167***	−0.163***
	(0.056)	(0.058)	(0.059)	(0.055)
Inflows of foreign inventors (lag 1, in log)	0.025	0.011	0.002	−0.010
	(0.033)	(0.031)	(0.033)	(0.034)
Trade (lag 1, in log)	0.024	0.021	0.019	0.019
	(0.040)	(0.038)	(0.034)	(0.032)
Inward non-innovative FDI (lag 1)	0.101***	0.063	0.070	0.026
	(0.038)	(0.040)	(0.044)	(0.047)
Inward non-innovative FDI (lag 2)		0.085**	0.076**	0.081**
		(0.041)	(0.034)	(0.038)
Inward non-innovative FDI (lag 3)			0.068	0.077
			(0.061)	(0.065)
Inward non-innovative FDI (lag 4)				0.066
				(0.064)
Inward non-innovative FDI (cumulative effect)	0.101***	0.148***	0.214***	0.250***
	(0.038)	(0.050)	(0.074)	(0.089)
Constant	2.485***	2.642***	2.641***	2.504***
	(0.645)	(0.650)	(0.646)	(0.590)
Pseudo-R2	0.686	0.690	0.693	0.695
Number of citing regions	615	609	602	595
Number of cited countries	66	66	65	65
Observations	67,742	65,766	63,486	61,159

Notes: PPML regression estimation. All models include citing region-year and cited country-year fixed effects. Standard errors clustered by citing region-cited country pairs are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Additive manufacturing	Artificial Intelligence	Big data	Blockchain	Computing infrastructure	Internet of Things	Robotics
3d print	artificial intellig	apache spark	altcoin	5th generation mobile	connected device	autonomous car
additive fabrication	artificial realit	apache cassandra	bitcoin	cloud application	connected home	autonomous underwater vehicle
additive layer manufacturing	augmented realit	big data	blockchain	cloud architecture	cyber-physical system	autonomous vehicle
additive manufacturing	automated reasoning	data center	cryptocurrenc	cloud broker	human-machine interface	auv
layered manufacturing	backpropagation	data centre	private blockchain	cloud client	industrial internet of things	chatbot
rapid prototyping	computer-mediated realit	hadoop	public blockchain	cloud computing	intelligent factor	drone
	computer vision	large-scale data		cloud infrastructure	internet of everything	humanoid robot
	data mining	mapreduce		cloud migration	internet of things	manipulator
	data science	massive data		cloud optimizer	iot	mobile manipulator
	deep learning			cloud portfolio	machine-to-enterprise	mobile robot
	expert system			cloud provider	machine-to-human	robot
	face detection			cloud server	machine-to-machine	robotic
	feature extraction			cloud service	pervasive sensing	self-driving car
	generative advesartial network			cloud sourcing	sensor network	self-driving vehicle
	gesture recognition			cloud storage	smart device	uav
	image classification			clould platform	smart factor	ugv
	image recognition			cognitive comput	smart home	uncrewed vehicle
	image segmentation			community cloud	smart sensor	unmanned aerial vehicle
	information retrieval			cyberinfrastructure	wearable	unmanned air vehicle
	intelligent machine			data-intensive comput	wireless body area network	unmanned ground vehicle
	kernel machine			dynamic cloud	wireless sensor network	unmanned spacecraft
	knowledge representation			federated cloud		unmanned underwater vehicles
	machine intelligence			fifth generation mobile		unmanned vehicle
	machine learning			hardware accelerator		unmanned aircraft system
	machine translation			high performance comput		
	meta-learning			hybrid cloud		
	mixed realit			hyper connectivity		
	multilayer perceptron			infrastructure as a service		
	natural language processing			inter-cloud computin		
	neural net			multi-cloud		
	object detection			neuromorphic comput		
	object identification			on-demand computing		
	object recognition			optical comput		
	pattern recognition			photonic comput		
	pose estimation			platform as a service		
	reinforcement learning			private cloud		
	semantic search			public cloud		
	semi-supervised learning			quantum comput		
	sentiment analysis			real-time comput		
	speech recognition			software as a service		
	statistical learning			supercomput		
	supervised learning					
	text classification					
	transfer learning					
	transformer network					
	unsupervised learning					
	virtual realit					
	voice recognition					

Figure A1. Digital technologies keywords by subdomain.

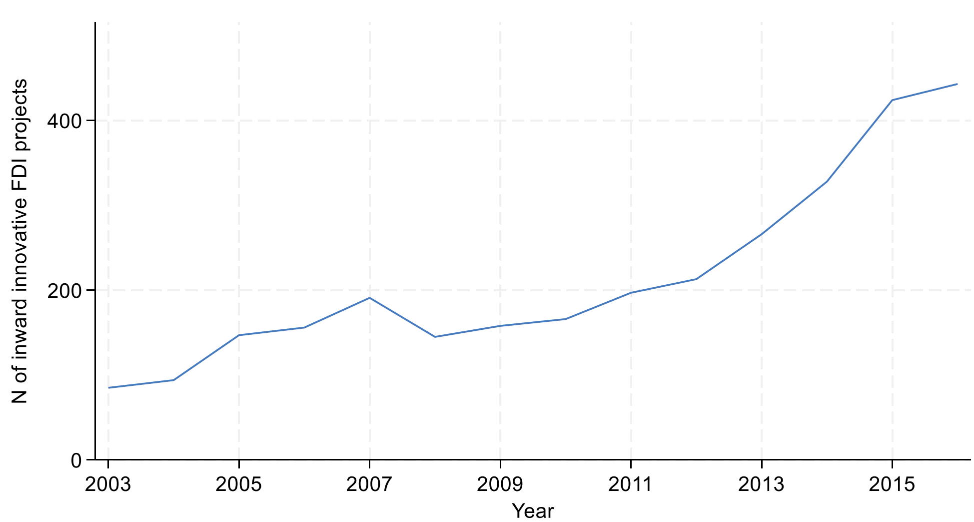

Figure A2. Inward innovative FDI over time, 2003–2016. Notes: inward innovative FDI projects to the EU27 Member States and the United Kingdom.