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The geography of Industry 4.0 technologies across European regions

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ABSTRACT

This paper investigates the spatial distribution of Industry 4.0 (I4.0) considering both region- and technology-specific factors. Focusing on patent data for four technologies at the core of I4.0 between 2000 and 2014, we provide evidence of their uneven distribution across NUTS-2 European regions. Our analysis confirms the role of regional absorptive capacity, cognitive and spatial proximity as drivers of I4.0 knowledge flows, but also indicates important variations among these technologies. Cumulated technological capabilities and spatial proximity exert a stronger effect on the diffusion of robots and 3D printing, whereas big data and the Internet of Things tend to be more spatially distributed.

KEYWORDS
Industry 4.0; knowledge spillovers; absorptive capacity; technology diffusion; relatedness

JEL O14, O33, R11, R58
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INTRODUCTION

Regions are going through a time of unprecedented technological change, which is causing profound transformations of industries, labour markets and society (Allen, 2017; Mitchell & Brynjolfsson, 2017; Organisation for Economic Co-operation and Development (OECD), 2016). Reflecting this, the last decade has seen increasing policy attention towards the opportunities offered by the application of disruptive enabling technologies into industrial activities (European Commission, 2010, 2017). In this context, the concept of Industry 4.0 (I4.0) has been put forward[1] to reflect a radical change in manufacturing processes defined by the integration of automation and digitalization into existing industries. There is a broad consensus around the potential of I4.0 to boost competitiveness and innovation across regions through the integration of new value-adding technologies into extant manufacturing activities, contributing to a significant renewal of localized industries (Bailey & De Propris, 2019; European Commission, 2017; Lafuente et al., 2019). In particular, the transformational processes of I4.0 have been associated with a group of interrelated technologies such as robots and three-dimensional (3D) printing, big data and the Internet of Things (IofT), which are driving the 'Fourth Industrial Revolution' (Kagermann et al., 2013; Martinelli et al., 2019; Schwab, 2016).

At the same time, growing research has also underlined potential challenges, pointing out the uneven geographical distribution of I4.0 research initiatives across European regions (Muscio & Ciffolilli, 2020). In this context, the spatial dynamics of I4.0 have become a key concern for economic geography and innovation scholars, as they connect to the ability of regions to reboot economic growth through embarking on a trajectory of radical technological change (Evangelista et al., 2018; Hervas-Oliver et al., 2019). However, there is still limited evidence on the geography of I4.0 and the factors defining the readiness of a region to embed I4.0 technologies, as well as possible differences across various I4.0 technologies (De Propris & Bailey, 2020). These are important research questions for understanding whether I4.0 may create diffused technological opportunities among regions, as opposed to a persistent gap between technology leaders and laggards (Barzotto et al., 2019a; De Propris & Bailey, 2020).

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This paper contributes to this nascent literature by analysing the diverse geographical distribution of I4.0 technologies and the drivers behind their diffusion across European regions. Conceptually, we follow the literature on formal knowledge production by focusing on technological invention as a specific subset of broader processes of regional innovation (Acs et al., 2002; Breschi, 2000; Capello & Lenzi, 2014). Within this framework, we build on cumulative perspectives in the geography of innovation (Kogler et al., 2017; Martin & Sunley, 2006; Rigby, 2015) to posit knowledge flows of I4.0 technologies are strongly defined by the heterogeneity of regional absorptive capacities as well as relatedness and spatial dynamics of knowledge spillovers. Furthermore, we argue that differences in the underlying characteristics of I4.0 technologies exert a crucial effect on both their spatial patterns and diffusion process. We provide evidence for these insights exploring all European Patent Office (EPO) patent applications across NUTS-2 regions in Europe between 2000 and 2014. Applying a classification of I4.0 technologies consistent with previous research (Martinelli et al., 2019; UK IP Office, 2013, p. 2014; 2014a, 2014b, 2014c), we analyse four key I4.0 technologies separately: robots and 3D printing, big data, and the IofT. First, we map the heterogeneous patterns of I4.0 technological invention in European regions. Then, in line with the literature on knowledge diffusion (Jaffe & Trajtenberg, 2002; Peri, 2005), we use patent citations to explore the determinants behind knowledge flows of I4.0 technologies.

Results point to diverse patterns of I4.0 technological capabilities and confirm the presence of important effects defined by regional absorptive capacity, cognitive as well as spatial proximity for their diffusion across European Union regions. At the same time, we observe the relative impact of these factors to differ across the various I4.0 technologies. Overall, our findings show the diffusion of I4.0 as being defined by an heterogenous set of technologies, pointing to their different role in enabling a smart manufacturing transformation within regions. The novelty of these results contributes to the emerging literature exploring the ability of regions to unlock the innovative potential of I4.0 across sectors (Barzotto et al., 2019a; Muscio & Ciffolilli, 2020), as well as discussing new industrial policies for enabling wider access to the transformative effects of I4.0 (Bianchi et al., 2019; Hervas-Oliver et al., 2019).

The remainder of the paper is structured as follows. We next present a conceptual framework focusing on the role of region- and technology-specific factors in explaining the geography of I4.0 patenting activities. In the following section we introduce the data and the methodology. Empirical findings are then presented and discussed. The final section concludes with a review of the findings before discussing some policy implications from the study.

LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

Regional drivers of technological activity

Regional scholars have long debated about the geographically and cognitively bounded nature of technological change (Asheim & Gertler, 2005; Jaffe et al., 1993; Malecki, 1991). In this literature, it is widely acknowledged that innovation is spatially embedded and that it is the result of recurring interactions and exchange of knowledge between different economic agents across the relational infrastructure of regions (Capello, 2002; Freeman, 1987; Lundvall, 1992; Storper, 2018). In particular, a large body of research has explored the production of technological invention as a function of localized knowledge endowments, corresponding to the stock of technological resources and capabilities within the region (Barzotto et al., 2019b; Capello & Lenzi, 2014; Jaffe et al., 1993; Moreno et al., 2005). Similarly, evolutionary perspectives have long posited that the innovative output of a region depends on exchanges and recombination among local pre-existing knowledge bases, defining a path- as well as a place-dependent trajectory of cumulated technological change (Bellandi et al., 2018b; Dosi, 1982; Martin & Sunley, 2006). In the context of technological transformation, the cumulated technological capabilities of a region can be seen as a predictor of the region's ability to integrate new technologies (Cohen & Levinthal, 1990; Giuliani, 2005). This cumulative nature of learning processes and technological upgrading at a regional level may lead to uneven distribution of new technology, being particularly marked in those regions that have integrated a larger stock of technology-specific knowledge into their pre-existing knowledge bases (Castellacci, 2008). Indeed, as each new technology entails a specific set of know-how and information, regions are expected to absorb and exploit new opportunities depending on previous technological capabilities accumulated within their knowledge bases (Boschma, 2017; Corradini, 2019). Accordingly, initial evidence indicates the distribution of I4.0 technologies is not homogenous across countries, regions and sectors (Ciffolilli & Muscio, 2018; Martinelli et al., 2019). Recent studies show that I4.0 technologies are most likely to diffuse within advanced manufacturing regions where there is greater availability of technological capabilities related to previous technological waves (World Bank, 2017).

The extent of knowledge cumulated within the region is not the only parameter to define its knowledge production function. In this regard, diversified regions characterized by a multiplicity of knowledge bases might show a higher capability to relate with new technological knowledge (Castaldi et al., 2015; Frenken et al., 2007). Diversified knowledge bases at a regional level might enable the exploration of cognitively and geographically scattered pipelines (Asheim et al., 2011; Bellandi et al., 2018b; Martin et al., 2018). These insights have been further explored within the evolutionary economic geography literature, suggesting knowledge recombination is not simply a function of variety in the technological space; rather, it is shaped by the similarity between pre-existing capabilities and the new technological knowledge (Boschma, 2017). Regions can be expected to have a higher capacity to integrate new technological knowledge into their innovative activities, when this is related to the local knowledge bases (Asheim et al., 2011; Boschma, 2017; Isaksen & Trippl, 2016). Here, the concept of relatedness has been defined to mainly reflect a cognitive dimension (Whittle & Kogler, 2019). Following this perspective, the assimilation of new technological knowledge strongly relies on optimal levels of cognitive proximity allowing both exploratory and exploitative learning processes (Nooteboom et al., 2007). High levels of cognitive proximity between the regional knowledge bases and the new technological knowledge may define a more effective absorptive capacity within regions (Isaksen, 2016; Martin & Sunley, 2006; Menzel & Fornahl, 2010). This suggests significant heterogeneity in the diffusion of I4.0 in favour of those regions whose knowledge bases are related to the new technology (Castellacci, 2008). In the same vein, Götz and Jankowska (2017) indicate only regions characterized by an adequate set of knowledge bases related to the field of information technology (IT) solutions, robotics, and so on, may be able to absorb and recombine the set of knowledge embodied in these technologies inside the region. At the same time, an upper bound to cognitive proximity may be important to ensure regions do not fall into lock-in effects (Boschma, 2005, 2017). In this sense, the positive effects of relatedness may be defined by an inverted 'U'-shaped function, as excessive cognitive proximity implies a lower level of novelty, and so it reduces the effect of technological knowledge on knowledge recombination (Corradini, 2019; Nooteboom et al., 2007).

Building on the concept of knowledge recombination, a complementary perspective could be defined based not on localized technologies, but the breadth of technological search from a region. In line with seminal studies at the firm level (Laursen & Salter, 2006; March, 1991), the breadth of technological search at the regional level defines the ability of the region to combine extensive exploration processes across a variety of knowledge bases, potentially leading to new technological trajectories (Boschma et al., 2017; Isaksen & Trippl, 2016). As regions scan broader sections of the technological landscape in their search processes, they could increase their ability to effectively leverage a wider set of technological knowledge, including opportunities offered by I4.0 technologies.

Underpinning these dynamics, the propensity of innovative activities to cluster spatially brings out the important role of places (Audretsch & Feldman, 2004). As indeed stressed by Audretsch and Feldman (2004, p. 2719), 'the marginal cost of transmitting information across geographic space has been rendered invariant by the revolution in telecommunications while the marginal cost of transmitting knowledge, especially tacit knowledge, is lowest with frequent social interaction, observation and communication'. Technology diffusion can be expected to occur depending on the proximity to other innovators and the access to new technological knowledge being created (Breschi & Lissoni, 2009). Thus, the distance from other regions developing I4.0 technologies might influence the ability to take advantage of knowledge spillovers (Almeida & Kogut, 1999; Jaffe et al., 1993), highlighting the importance of a context-specific nature in knowledge flows of I4.0 technologies.

The role of technology-specific characteristics

In the analysis of regional technological change, scholars have long focused on the localized nature of innovative activities and the role of regional innovative capabilities to catch up with new technological opportunities (Bellandi et al., 2018a; Hassink et al., 2019). While regional learning processes and knowledge bases certainly inform about the ability of regions to seize opportunities for innovation, technology-specific factors may play an important role as well. However, the heterogeneity across technologies and their underlying characteristics has received limited attention in policy debates on I4.0, where diverse technologies tend to be discussed as a homogenous set (Bailey & De Propris, 2019; Ciffolilli & Muscio, 2018).

Technology studies have long discussed how some inventions, usually more original and connected to basic science (Corradini & De Propris, 2017; Trajtenberg et al., 1997), have a wider applicability and stronger penetration across a broader set of technological domains. Notably, general-purpose technologies (GPTs) are characterized by their broad applicability across the economy and their ability to establish new complementarities among sectors (Bresnahan & Trajtenberg, 1995). GPTs have an extraordinary potential to connect with a larger set of sector-specific knowledge bases, expanding the scope for knowledge search. These effects have been found to increase the likelihood of whole new technological trajectories entering a region (Evangelista et al., 2018; Montresor & Quatraro, 2017). Similarly, technologies enabling new complementarities among sectors and bringing closer previously unrelated sectors have been associated with more novel recombination and radical innovation (Corradini & De Propris, 2017). In line with this approach, the adoption of system-wide 'key enabling technologies' (KETs) has been presented as a major source of economic benefits by the European Commission (2011) and also by a number of scholars (Evangelista et al., 2018; Muscio & Ciffolilli, 2020). Many scholars have highlighted the enabling role of I4.0 technologies and the characteristics making them comparable with GPTs (Goldfarb et al., 2019; Martinelli et al., 2019; Simon, 2019). Yet, a key consideration is that not all enabling technologies share the same transformative potential (Teece, 2018). For example, a recent study by Martinelli et al. (2019) analyses differences among six enabling technologies based on several dimensions, including their original recombination of pre-existing industrial knowledge bases and their application in downstream sectors.

The above discussion suggests technology- and region-specific factors should be jointly considered to explain the ability of regions to generate innovations from the absorption and recombination of new technological knowledge (Diodato & Morrison, 2019). Reflecting the insights on technological regimes and *widening* as opposed to *deepening* patterns of innovation (Breschi, 2000), the potential for I4.0 to trigger new innovative activities may be defined by the degree to which these technologies rely on the region's pre-existing knowledge bases. Accordingly, recent evidence shows that some of these technologies, such as robots and 3D printing, are characterized by high levels of cumulativeness, suggesting their creation is largely concentrated in specific industrial contexts (Lechevalier et al., 2014). The stronger association with industrial knowledge bases also reveals that the knowledge embodied in these technologies is highly specialized and 'sticky', which makes opportunities for knowledge flows more difficult to occur (Breschi, 2000; Diodato & Morrison, 2019; Malerba & Orsenigo, 1996). On the other hand, Rong et al. (2015) recognize the potential of IofT to enable cross-industry, cross-discipline knowledge recombination opportunities through complex interactions among an array of different contexts (e.g., private and domestic, industrial, service related). Furthermore, IofT technologies open up to the generation and collection of growing volumes of data at unprecedented rates, and they tend to be associated with advanced capabilities to leverage big data analytics as a key source of information (Mourtzis et al., 2016). Differently from robots and 3D printing, this suggests that the technological knowledge of IofT and big data is less specific and can more easily flow across space and sectors generating more distributed innovative activities (Malerba & Orsenigo, 1996).

Following these insights, we argue regional absorptive capacity defined by higher cumulated technological capabilities and relatedness between a specific I4.0 technology and the regional knowledge base may be expected to play a less important role for the diffusion of I4.0 technologies characterized by wider applicability and lower barriers to entry, in line with a *widening* pattern of innovation (Breschi, 2000). This may be the case for digital technologies such as big data and IofT (Teece, 2018). Conversely, the recombination of technological knowledge from robots and 3D printing, more strongly associated with a specific set of advanced manufacturing, may be more likely in the presence of higher relatedness with the regional technological structure and stronger cumulativeness with respect to previous technological activity. Reflecting a *deepening* pattern of innovation due to lower pervasiveness across various industries and spatially concentrated competencies (Breschi, 2000), geographical proximity may also be more important for these technologies.

DATA AND METHODOLOGY

In order to investigate the spatial patterns of I4.0 creation and diffusion across European regions, we make use of patent data from the PATSTAT-CRIOS database.[2] Patent data have long been used in the literature to explore technological change as well as knowledge spillovers across regions (Barzotto et al., 2019a; Maurseth & Verspagen, 2002; Moreno et al., 2005). This is due to the granular information they offer on the location, time and specific technological classification of the invention, whilst marking the presence of a significant inventive step. Patent data also present some well-known limitations for empirical analysis. While they offer an effective proxy for technological invention, they may not fully capture the broader set of innovation activities resulting, for example, from learning by doing, by using and by interacting processes (Jensen et al., 2007), or the application of the underlying technologies within production activities (Griliches, 1990). However, previous literature indicates that by providing a view on processes of technological knowledge creation, patents offer important insights on regional innovation activities (Acs et al., 2002). In particular, patents have been found to offer important insights for the study of technological knowledge flows and their diffusion (Jaffe & Trajtenberg, 2002; Peri, 2005).[3]

In this paper, we use patent data covering all applications at the EPO across 283 NUTS-2 regions in Europe for the period 2000–14.[4] Patents are allocated to NUTS-2 regions based on fractional count of inventors' location and technological class of the patent. To identify I4.0 technologies on robots, 3D printing, big data and the IofT, we make use of the technological classification provided within patent applications. We use combined technological classes at the eight-digit level from both the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC) following research conducted by the UK Patent Office and recent studies on I4.0 technologies (Ardito et al., 2018; Martinelli et al., 2019). The full list of IPC and CPC classes for each group are reported in Table A1 in Appendix A in the supplemental data online.

The analysis consists of two steps. In the first one, this dataset is used to provide some stylized facts on the geography of I4.0, offering descriptive information on the location of invention of the four I4.0 technology groups identified and their spatial autocorrelation. In the second, we present an exploratory model[5] for estimating the likelihood of I4.0 patents to contribute to new technological inventions within the region. The model is defined as follows:

$$\begin{aligned} Y_{irt} = \beta_0 + \ &\beta_1 Kstock_{rt} + \beta_2 I40Pat_{irt} + \beta_3 Related_{irt} \\ &+ \beta_4 Related{*}Related_{irt} + \ \beta_5 RegDiv_{rt} \\ &+ \beta_6 RegBreadth_{rt} + \beta_7 I40Pat_{100kmirt} \\ &+ \beta_8 X_{rt} + \delta_r + \delta_t + \epsilon_{rt} \end{aligned} \tag{1}$$

Considering the limited number of I4.0-related patents, we define our dependent variable Y for each I4.0 patent group i in region r in time t as a dichotomous variable equal to 1 if any patent within the region presents a forward citation to any EPO patent in the specific I4.0 group i,[6] and 0 otherwise. In other words, this variable captures the presence of knowledge flows from any existing EPO I4.0 patent to patenting activities within the region, indicating whether regions were able to identify and use I4.0 technological knowledge in developing their patents. This is applied to the four selected i categories:

robots, 3D printing, big data and IofT. In line with the binary nature of this variable, we estimate equation (1) using a probit model with cluster robust standard errors at the NUTS-2 level.[7]

The right-end side of the model contains variables defining the probability of citing a I4.0 patent across technological activities in region *r*. In particular, we have the regional knowledge stock (*K_STOCK*) as a proxy of the region's absorptive capacity, defined as the cumulated number of patents weighted by total population with an annual depreciation rate set, as customary, at 15%.[8] We also include a specific measure of absorptive capacity for I4.0 technologies (*I40_PAT*), defined as the number of patents in each of the four I4.0 groups, also weighted by total population.

To capture the importance of cognitive proximity between knowledge bases for new knowledge creation, we use a measure of relatedness between the specific I4.0 technology and the broader set of patents in a region. In line with Kogler et al. (2017), we first develop a standardized co-occurrence matrix S_{ij} as follows:

$$S_{ij} = \frac{N_{ij}}{\sqrt{N_i * N_j}} \tag{2}$$

where N_{ij} represents co-class counts among all pairs of IPC technological classes. Our measure *RELATED* is then defined as the average standardized proximity between the specific I4.0 technology and all other classes in the region weighted by the respective number of patents. A quadratic term for *RELATED* is also added to control for diminishing returns reflecting possible lock-in effects in the presence of excessive relatedness (Corradini, 2019). We then add a measure of regional technological diversification (*REG_DIV*) to proxy the role of different sector-specific knowledge bases within regions, calculated as a normalized Shannon entropy index:

$$\text{REG\_DIV} = -\sum_{i}^{n} \frac{s_i \ln s_i}{\ln n} \tag{3}$$

where s is the share of patents in class i; and n is the total number of patent classes in the region.

To include the role of technological search breath borrowed from firm level studies (Fleming, 2001; Fleming & Sorenson, 2004), we propose a similar normalized index of diversity built on forward citations in the region:

$$\text{REG\_BREATH} = -\sum_{i}^{n} \frac{c_i \ln c_i}{\ln n} \tag{4}$$

where c is the share of forward citations in class i; and n is the total number of classes cited in the region. Thus, *REG_BREATH* measures the heterogeneity of technological classes cited within regional patenting activities, reflecting their capabilities to monitor and absorb knowledge bases from a diverse set of technological fields.

To capture spatial proximity effects, we add a spatial lagged variable for *I40_PAT* to proxy possible knowledge spillovers from neighbouring regions in the development of I4.0 technologies. This measure is calculated using a spatial weight matrix with the threshold distance set at both 100 and 200 km values. Finally, we add a set of controls reflecting the percentage of population in science and technology employment (*TECH_EMPL*), population growth (*POP_GROW*) and population density (*PDENS*) expressed in 10,000 people/km^2. Country and time fixed effects are also included in the model. For descriptive statistics for all variables, see Table A2 in Appendix A in the supplemental data online.

RESULTS AND DISCUSSION

Spatial patterns in the creation of I4.0 technologies

We start exploring the geography of I4.0 in Europe by looking at the spatial distribution of patents in the four categories of I4.0 technologies across NUTS-2 regions. This is depicted in Figure 1, which shows the average fractional number of I4.0 technologies for the period 2000–14. We observe a clear and marked difference between robots and 3D printing patents when compared with the spatial distribution of big data and the IofT technologies.

The first group reveals a much higher concentration around Central European regions. In particular, robots and 3D printing seem strongly connected to regional systems with specific manufacturing expertise and where such innovation is first used, such as automotive in the south-west of Germany (Brenner, 2006; Plum & Hassink, 2013), and transport and medical instruments in the south-east of France (Andersson et al., 2013; Guisard et al., 2010). Conversely, big data and IofT patents are more widely distributed across regions. This latter pattern of I4.0 creation presents higher activities in highly urbanized regions in various European countries, providing initial evidence this latter group may have wider applicability in line with digital technologies and information and communication technology (ICT) (Castellacci et al., 2019). These differences are similarly suggested by the measure of co-occurrence defined by *RELATED* (see Table A2 in Appendix A in the supplemental data online). This is equal to 0.58 for robots, while the average for 3D printing is 0.75. Conversely, we find much higher levels for big data, equal to 1.64, and IofT with 2.61.

The evolution of I4.0 patenting between 2000 and 2014 is depicted in Figure 2. In Figure 2(a), we see these technologies represent a small percentage of total patenting. We still observe differences between robots and 3D printing, which represent a smaller percentage but are slightly increasing versus big data and IofT. In Figure 2(b), we report the Gini index for the four groups, showing the aspatial concentration in their distribution across regions. I4.0 technologies remain more concentrated in specific regions than overall patenting activities, whose concentration averages 0.7. In particular, robot technologies are the most concentrated, in contrast to big data, though the gap is reducing over the period considered.

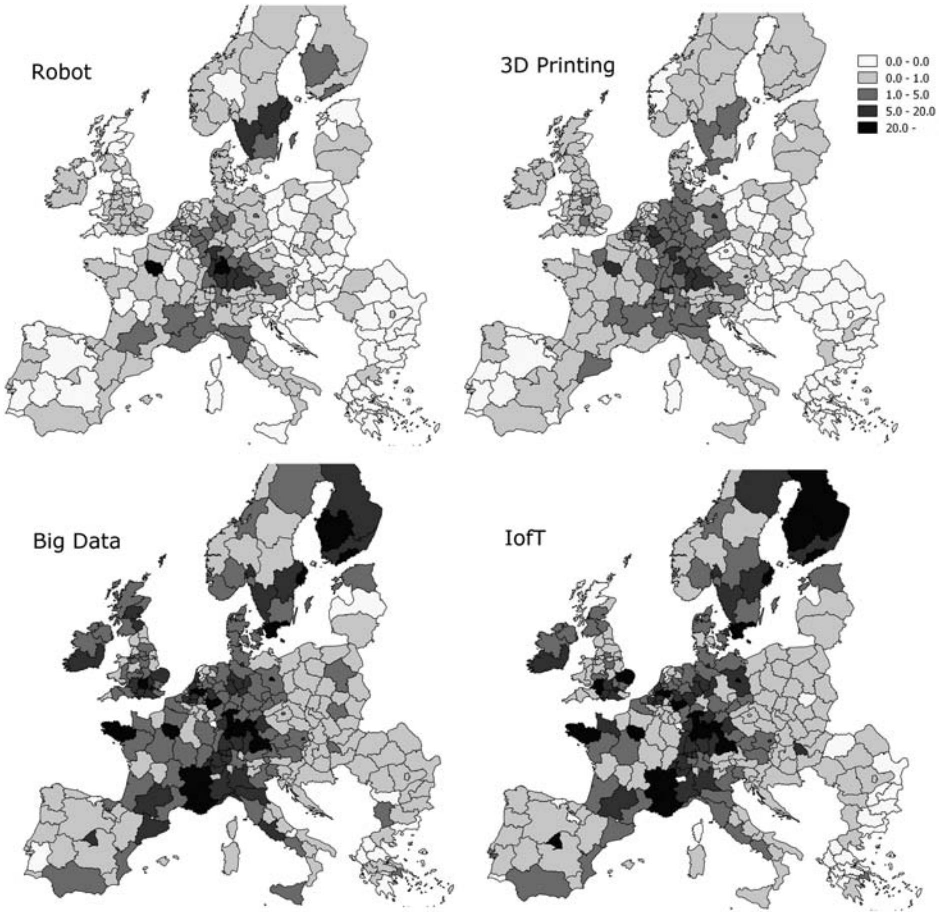

Figure 1. Number of patents in Industry 4.0 (I4.0) technologies: averages, 2000–14.

To investigate differences in spatial concentration across the four I4.0 technologies, we look at a Moran scatterplot reflecting the relationship between standardized values (z) for each I4.0 technology and a row-standardized spatial weight matrix Wz. This is shown in Figure 3, where the slope for each graph represents the respective spatial autocorrelation for the four I4.0 groups.[9] As suggested by Figure 1, we observe a stronger spatial relation for robots and 3D printing, while spatial autocorrelation is less steep for big data and even less for IofT patents.[10]

Regional determinants of I4.0 diffusion

In this section, we explore the conditional impact of the various regional and technological specific factors driving the diffusion of I4.0 technologies across the 283 NUTS-2 regions in Europe. We present the results of the probit model presented in the third section. These are reported in Table 1.[11] For robustness, we also report the results using logit regression with regional fixed effects in Table 2, columns 1–4. In columns 5–8 of Table 2, we report the results using an alternative definition of diffusion, labelled *I40_ENTRY*, defined as a binary variable equal

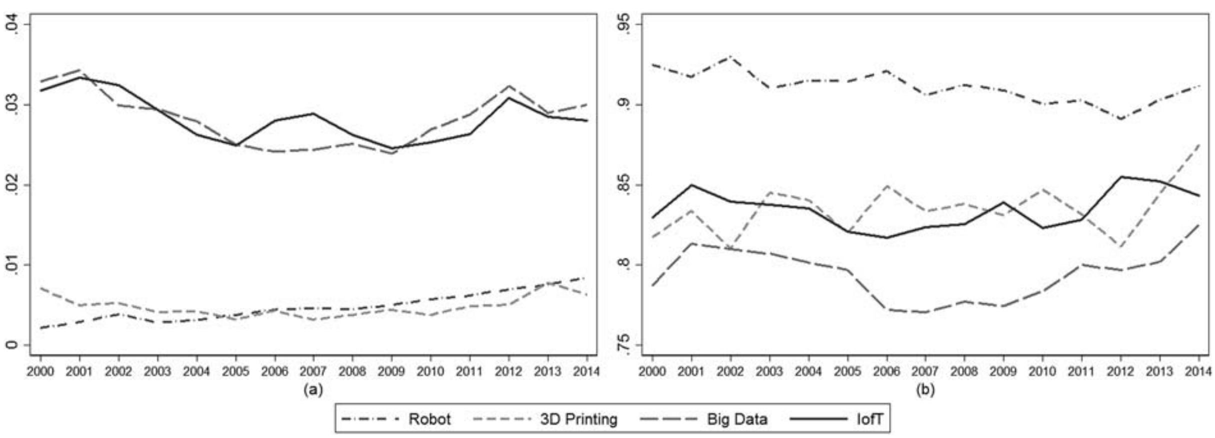

Figure 2. Relative number of Industry 4.0 (I4.0) patents over total (a); and concentration (b).

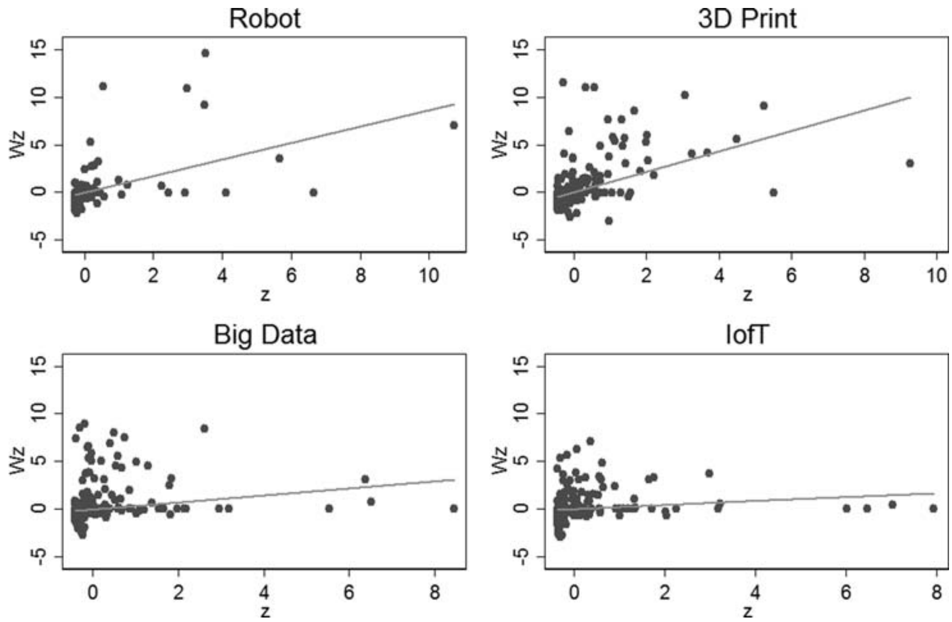

Figure 3. Moran scatter plots for Industry 4.0 (I4.0) technologies.

to 1 for regions starting to cite at least one I4.0 patent for three years in a row.

In line with our conceptual framework, variables of absorptive capacity have a positive effect on the likelihood of I4.0 knowledge flows into regional processes of technological invention. This is confirmed by the positive and statistically significant effect of knowledge stock (*K_STOCK*) on the presence of forward citations of I4.0 patents for all four technologies. This effect is slightly less pronounced and statistically different for robots.[12] At the same time, considering the specific knowledge stock around I4.0 technologies (*I40_PAT*), we find a significant and positive effect only for robots and big data, the former being markedly stronger and statistically different from the others. Together, these results confirm the importance of technological absorptive capacity and cumulativeness in regional innovation. They also seem to be more prominent for robots, which benefits particularly from cumulated capabilities in its own field, and 3D printing, which is more strongly supported by wider regional technological capabilities. Overall, this might imply that the diffusion of robots and 3D printing depends more strongly on the nature of local cumulated technological capabilities compared to IofT and big data, thereby suggesting a more limited applicability across various knowledge bases.

The next set of regressors focuses on the effect of relatedness and variety. Looking at the coefficients of relatedness, our results point to an inverted-‘U’ effect of technological relatedness between I.40 patents and the wider set of patents in the region. This reflects previous evidence on the importance of cognitive proximity for absorbing technological knowledge bases and introducing I4.0 technologies across regions. This result confirms the insights of Götz and Jankowska (2017) highlighting that regions anchored to knowledge bases related to IT solutions, robotics, automatics and so on, might have significant advantages in enabling I4.0 transformation. At the same time, it also reflects previous studies indicating too much relatedness may reduce the set of combinatorial opportunities leading to lock-in effects (Corradini, 2019; Martin, 2010).

Focusing on the specific technologies, we observe statistically significant differences around the effect of relatedness confirming that technology-specific factors can also affect the diffusion of I4.0 across regions. Relatedness seems to play a more prominent role for the diffusion of 3D printing technologies as opposed to IofT. Effects for robots and big data are in the middle. Overall, considering the much stronger effect of previous I4.0 patents (*I40_PAT*) for robot technologies, these results support the idea of a more specific nature of robots and 3D printing and a wider applicability of big data and IofT. This is also supported by the results from the FE logit regression reported in Table 2 (columns 1–4) and the alternative specification based on *I40_Entry* (Table 2, columns 5–8). Conversely, we do not find a significant effect of regional technological diversification (*REG_DIV*), suggesting that the presence of multiple knowledge bases does not necessarily lead to increased diffusion of I4.0 technologies. In fact, we find a negative effect for 3D printing. These results (i.e., *REG_DIV* and *RELATED*) confirm the importance of the configuration of the inherited technological capabilities and the path-dependent nature of technological change during this disruptive transformation of regions. Here, relatedness is indeed important in sustaining knowledge flows, rather than simply diversity of knowledge bases for connecting to new opportunities.[13] However, consistently with the cognitive distance theory (Nooteboom et al., 2007), too much proximity reduces the novelty power of combinative opportunities at a regional level. These findings are overall consistent with the results reported in Table 2.

Table 1. Probit regression results across Industry 4.0 (I4.0) technologies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robots		3D printing		Big data		Internet of Things	
K_STOCK	0.0007***	0.0007***	0.0014***	0.0015***	0.0009***	0.0009***	0.0012***	0.0011***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
I40_PAT	0.2328**	0.2295**	0.0778	0.1000	0.0825**	0.0824***	0.0559	0.0555*
	(0.1171)	(0.1158)	(0.0837)	(0.0899)	(0.0322)	(0.0304)	(0.0360)	(0.0345)
RELATED	0.1160***	0.1164***	0.3093***	0.3225***	0.1271***	0.1282***	0.0639***	0.0644***
	(0.0209)	(0.0209)	(0.0524)	(0.0534)	(0.0162)	(0.0166)	(0.0053)	(0.0054)
RELATED^2	−0.0072***	−0.0073***	−0.0793***	−0.0830***	−0.0126***	−0.0128***	−0.0020***	−0.0020***
	(0.0026)	(0.0026)	(0.0200)	(0.0204)	(0.0029)	(0.0030)	(0.0003)	(0.0003)
REG_DIV	−0.1019	−0.0976	−0.1436*	−0.1513*	−0.0694	−0.0753	0.0152	0.0050
	(0.0875)	(0.0892)	(0.0869)	(0.0885)	(0.0771)	(0.0779)	(0.0801)	(0.0803)
REG_BREADTH	0.1541**	0.1551**	0.1419***	0.1457***	0.1604***	0.1589***	0.1283***	0.1253***
	(0.0644)	(0.0646)	(0.0441)	(0.0450)	(0.0461)	(0.0464)	(0.0409)	(0.0416)
I40_PAT_LAG100	0.0048**		0.0058***		0.0011*		0.0021***	
	(0.0021)		(0.0018)		(0.0006)		(0.0005)	
I40_PAT_LAG200		0.0010*		−0.0005		0.0005**		0.0009***
		(0.0006)		(0.0007)		(0.0002)		(0.0002)
TECH_EMPL	0.0220***	0.0219***	0.0233***	0.0220***	0.0352***	0.0348***	0.0296***	0.0287***
	(0.0080)	(0.0081)	(0.0082)	(0.0083)	(0.0095)	(0.0096)	(0.0084)	(0.0085)
POP_GROW	0.0012	0.0012	−0.0022*	−0.0019	−0.0014	−0.0017	0.0035**	0.0033**
	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0016)	(0.0016)	(0.0015)	(0.0016)
PDENS	0.0118*	0.0136**	0.0180	0.0189	0.0572**	0.0627**	0.0297*	0.0368**
	(0.0069)	(0.0068)	(0.0125)	(0.0123)	(0.0247)	(0.0276)	(0.0165)	(0.0169)
Pseudo-R^2	0.193	0.192	0.199	0.194	0.185	0.184	0.258	0.255
N	2846	2846	2945	2945	3003	3003	3024	3024
Regions	206	206	214	214	219	219	221	211

Note: Cluster robust standard errors are shown in parentheses. All regressions include time and country fixed effects. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2. Logit fixed effects and probit Industry 4.0 (I4.0) entry regression results across I4.0 technologies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fixed effects: *I40_CIT*				Probit: *I40_Entry*			
	Robots	**3D printing**	**Big data**	**Internet of Things**	**Robots**	**3D printing**	**Big data**	**Internet of Things**
K_STOCK	0.0008**	0.0013***	0.0004	0.0004	0.0003***	0.0014***	0.0001	0.0008***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0001)	(0.0003)	(0.0003)	(0.0002)
I40_PAT	0.2524	0.0141	0.0248	−0.0042	0.0419	0.0595	0.0698**	0.1147**
	(0.1621)	(0.1053)	(0.0393)	(0.0459)	(0.0401)	(0.0594)	(0.0276)	(0.0472)
RELATED	0.2611***	0.3979***	0.1230***	0.0729***	0.2072***	0.2215***	0.0257**	0.0202***
	(0.0631)	(0.0921)	(0.0265)	(0.0176)	(0.0592)	(0.0643)	(0.0123)	(0.0059)
RELATED^2	−0.0159***	−0.0980***	−0.0123***	−0.0021***	−0.0907***	−0.0737***	−0.0020*	−0.0007*
	(0.0056)	(0.0337)	(0.0037)	(0.0006)	(0.0343)	(0.0285)	(0.0011)	(0.0004)
REG_DIV	−0.2894	−0.2502	0.0145	0.0368	−0.0643	−0.2259**	−0.1481**	−0.1095*
	(0.3653)	(0.1955)	(0.1447)	(0.1424)	(0.0918)	(0.1104)	(0.0691)	(0.0649)
REG_BREADTH	0.2998	0.2013*	0.1410*	0.1362*	0.0083	0.1080	0.0462	0.0640
	(0.2034)	(0.1179)	(0.0889)	(0.0795)	(0.0544)	(0.0814)	(0.0505)	(0.0601)
I40_PAT_LAG100	0.0054	0.0095**	0.0013*	0.0039***	0.0017*	0.0002	0.0003*	0.0011***
	(0.0079)	(0.0042)	(0.0007)	(0.0012)	(0.0007)	(0.0012)	(0.0001)	(0.0003)
TECH_EMPL	0.0007	0.0175	0.0038	0.0041	0.0129**	0.0150*	0.0450***	−0.0004
	(0.0243)	(0.0177)	(0.0161)	(0.0162)	(0.0057)	(0.0080)	(0.0103)	(0.0091)
POP_GROW	−0.0011	−0.0065**	−0.0052**	0.0047*	0.0014**	−0.0012	0.0026**	0.0022*
	(0.0035)	(0.0026)	(0.0024)	(0.0027)	(0.0006)	(0.0015)	(0.0011)	(0.0012)
PDENS	−0.1419	−1.3984**	−1.6779**	−1.2478*	−0.0045	0.0098	0.0294***	0.0452***
	(0.2391)	(0.5496)	(0.7020)	(0.7520)	(0.0051)	(0.0107)	(0.0107)	(0.0150)
Pseudo-R^2	0.604	0.615	0.566	0.653	0.406	0.454	0.505	0.502
N	1899	2016	2006	2048	1379	1060	1072	1038
Regions	131	144	143	147	156	161	185	188

Note: Robust standard errors are shown in parentheses. Logit regressions include time and regional fixed effects. Probit regressions include country and time fixed effects. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Considering *REG_BREADTH*, which captures the diversity in the set of technological classes cited within regional patenting activities, results suggest that the extent of technological search across different patent classes is a significant determinant of I4.0 diffusion. Regions scanning opportunities from a higher number of sources of technological knowledge seem to be more able to take advantage of I4.0 technologies than regions characterized by narrower and localized, in a cognitive sense, search processes. While the impact of *REG_BREADTH* is slightly higher for robots and big data, differences across the four I4.0 groups are not statistically different. This is also supported by results from logit regression in Table 2, though the effect of *REG_BREADTH* is no longer significant in the model based on *I40_ENTRY* (Table 2, columns 5–8).

Finally, we consider the role of spatial proximity in enabling spillovers of I4.0 knowledge by looking at the impact of spatial lags defined by 100 and 200 km thresholds. Our results indicate that being close to I4.0 knowledge has a positive and statistically significant effect for all four technologies. In line with the literature on technological spillovers (Acs et al., 2002; Audretsch & Feldman, 2004), these effects become more subdued as the distance increases. More interestingly, as suggested by Moran's *I* statistics (see Table 3A in Appendix A in the supplemental data online), there are significant spatial dynamics playing a role in I4.0 technologies. Indeed, the impact of spatial distance is more marked for robots and 3D printing as opposed to big data and IofT, with the difference across the two groups being statistically significant. This evidence reinforces insights considering knowledge flows of the former group as being more dependent upon clustering dynamics and demand-pull effects, emphasizing the important role of places even in the I4.0 era.

CONCLUSIONS

This paper contributes to the growing debate between scholars and policymakers on I4.0 (De Propris & Bailey, 2020; European Commission, 2017; Evangelista et al., 2018) offering novel insights on the geography of I4.0 technologies. Merging perspectives on regional absorptive capacity, evolutionary economic geography and technology specific dynamics, our analysis has shown that the interplay of both technology and regional specific factors play a crucial role in shaping the distribution and diffusion of I4.0 technologies across regions.

Exploring all EPO patent applications for almost 300 NUTS-2 regions in Europe in the period 2000–14, the results point to critical differences in the geographical location of I4.0 technologies and confirm the important role of cumulated regional technological capabilities, relatedness, technological search breadth and spatial proximity to I4.0 invention in determining the diffusion of I4.0 technologies. We also show these effects differ across various I4.0 technologies. In particular, robots and 3D printing technologies remain strongly concentrated in some regions with relatedness and cumulativeness as well as spatial proximity playing a stronger effect on their diffusion. In contrast, patents on big data and IofT appear to be more distributed across European Union regions, with cumulated technological capabilities (i.e., regional absorptive capacity and relatedness) and spatial proximity having a more moderate effect. The former seems to be strongly related to the traditional endowment of high-tech manufacturing capabilities. On the other hand, the latter can be related to the lower capital-intensive nature of innovation in these fields and their broader technological applicability (Barzotto et al., 2019a; Teece, 2018). These findings indicate that the diffusion of I4.0 may be markedly uneven across regions, reflecting regional differences as well as heterogeneity in the technologies behind I4.0 transformation.

These results offer important insights for policy debates focusing on the opportunities offered by I4.0 to promote widespread technological change across regions. First, I4.0 technologies do not seem to disrupt the spatial patterns of technological invention across European regions. The risks of persistent gaps between technology leaders and laggards among these regions are high, and industrial policies may be crucial to ensure the benefits of I4.0 are widespread across regions (Bailey & De Propris, 2019; Barzotto et al., 2019a). Policy initiatives need to consider the diffusion of I4.0 technologies can vary significantly among regions, depending on a combination of pre-existing technological capabilities and the degree of specificity of each I4.0 technology. In line with evolutionary perspectives (Kogler et al., 2017; Rigby, 2015), policies should be designed considering that regions will have a higher potential to absorb I4.0 if they possess related technological capabilities. At the same time, efforts may be more effective when designed considering differences in the applicability of the specific I4.0 technologies. Our results also indicate supporting wider technological search – through novel networks or university research (Corradini & De Propris, 2017; Guerzoni et al., 2014) – may partially counterbalance path-dependence effects. Similarly, platform-like instruments and innovation intermediaries might be identified as policy actions facilitating uncommon interactions (Janssen & Frenken, 2019). Finally, the differentiated role of spatial proximity suggests efforts on technological collaboration may also enhance I4.0 adoption by breaking down localized patterns of diffusion, which may be particularly important for lagging regions with less defined technological capabilities (Barzotto et al., 2019b). Crucially, our findings underline policy makers should consider initiatives based on these elements carefully, taking into account the heterogeneity characterizing the various I4.0 technologies and the implications these exert on diffusion processes.

The results should be considered in light of the caveats inherent to the use of patent data and the perspective of the analysis presented, which define interesting avenues for further research. While patents offer a view on knowledge flows in the process of technological invention of I4.0, complementary perspectives are required to show

how these new technologies are embedded within industrial production activities and further innovation arising in the application of I4.0 on factory floors (Szalavetz, 2019). This is fundamental, as the link between technological invention and broader processes of innovation may be heterogeneous at the regional level (Capello & Lenzi, 2014). Similarly, I4.0 entails an increasing integration of manufacturing and services activities. Our results suggest servitization studies should consider potential differences defined by the diverse nature of the technologies underpinning I4.0 transformations. At the technology level, we need more insights on possible multiplier effects across I4.0 technologies, and their differential impact in terms of enabling or bridging effects (Corradini & De Propris, 2017; Montresor & Quatraro, 2017). This also suggests studying the role of University patents for the development as well as diffusion of I4.0 technologies may be an interesting direction for further research. Finally, following the evidence presented on spatial lags in I4.0 diffusion, further combinative opportunities may be identified through the analysis of extra-regional collaborations or inventors' mobility. This may be particularly important to support the diffusion of I4.0 in lagging regions (Barzotto et al., 2019b). While several research questions remain open, our paper contributes to the debate on the opportunities offered by I4.0 highlighting its transformative effects should not be discussed as a homogenous process.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. The term 'Industry 4.0' was first introduced by Kagermann et al. (2013).
2. For more details on PATSTAT-CRIOS and the harmonization of patent data, see Coffano and Tarasconi (2014).
3. As we discuss in the fifth section and in line with the different contributions in this special issue, we readily recognize complementary studies are necessary to define a broader understanding of the I4.0 revolution.
4. Time is based on patents' priority date, which is the closest to the date of invention (Hinze & Schmoch, 2004).
5. The model is not intended to provide causal evidence but rather to offer stylized facts on established determinants of technology diffusion in regional studies in the context of I4.0.
6. We exclude the I4.0 sector itself from this. The results are robust when all sectors are included.
7. The results are consistent across different specifications, including the total number of forward citations and a fractional logit model based on forward citations to the specific I4.0 technology over all forward citations in the region for year t.
8. This measure is defined using the perpetual inventory method: $K\_STOCK_{rt} = N_{rt} + (1 - \delta)K\_stock_{rt} - 1$, where δ is the depreciation rate set at 15%. I4.0 patents are excluded from this measure.
9. Threshold distance for the spatial weight matrix is set at 100 km.
10. For the specific Moran's I statistics for each technology, see Table A3 in Appendix A in the supplemental data online.
11. Considering the non-linear nature of probit models, we report all results as marginal effects. These measure the percentage change in the probability of $y = 1$ for a one-unit change in the regressor, allowing for a direct interpretation of the impact of each variable in the model.
12. Tests for statistical differences in regression coefficients across the four technology groups are based on seemingly unrelated regressions. The results are available from the authors upon request.
13. Even when removing correlated variables such as relatedness, this result holds.

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