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Mapping the potential of EU regions to contribute to Industry 4.0

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ABSTRACT

This paper aims to identify the future Industry 4.0 centers of knowledge production in Europe. We expect Industry 4.0 Technologies (I4Ts) to thrive in regions where they can draw on local resources from related technologies. We use OECD-REGPAT data to identify I4T-related technologies, and find that I4Ts are located at the periphery of the knowledge space. Regions with a high potential in terms of I4T-related technologies were more likely to diversify successfully in new I4Ts in the period 2002-2016. We find big differences across EU regions: some show high but most regions show weak I4T potential.

KEY WORDS: Industry 4.0, relatedness, patents, knowledge space, regional diversification, EU regions

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1. INTRODUCTION

In the last two centuries, Europe has been subject to three Industrial Revolutions. These transformative periods opened new windows of opportunities of economic growth and prosperity, leading to the rise of new economic leaders (Perez and Soete 1988). These revolutions led to major transformations in the geography of knowledge and innovation (Marshall 1987; Hall and Preston 1988). The Third Revolution led to the emergence of the Sunbelt states (and Silicon Valley in particular) and the decline of manufacturing regions in the Rust Belt states in the US (Markusen et al. 1986; Scott 1988; Lecuyer 2006). Europe underwent similar regional dynamics, where the South-East in the UK and Bavaria in Germany presented themselves as the new centers of excellence and innovation.

We are currently undergoing a Fourth Industrial Revolution that is often associated with cyber-physical systems, the Internet of Things, robotics, and artificial intelligence (Liao et al. 2017; Lu 2017; Ménière et al. 2017). These key technologies will affect a wide range of sectors of the economy. Studies have stressed that a broad range of jobs and job tasks in an economy may be automated, including non-routine tasks such as using big data to diagnose diseases or selecting job applicants for interviews (Bessen et al. 2019). As in studies on previous Industrial Revolutions, there is a lot of emphasis on possible negative effects, like the negative consequences of automation in terms of number and types of jobs that are expected to be displaced or under threat (see Frey and Osborne 2016; Bessen et al. 2019).

The Fourth Industrial Revolution may have the same dramatic effects on the geography of knowledge and innovation in Europe as the previous three Industrial Revolutions. Muro et al. (2019) found differences across metropolitan regions in the US with respect to their exposure to automation-driven task replacement. More in general, the literature suggests more often than not that Industry 4.0 will open windows of opportunities for many regions, make new regional leaders, and has the potential to shift the geography of knowledge production in Europe (Gress and Kalafsky 2015; Ménière et al. 2017; Strange and Zucchella 2017; Ciffolilli and Muscio 2018). The big question is how.

This paper aims to identify the future Industry 4.0 centers of knowledge production in Europe. First, we use patent data from the OECD-REGPAT database (edition March 2018) to identify patents in Industry 4.0 Technologies (I4T) for 290 NUTS2 EU regions over the period 2002-2016. This enables us to identify the current Industry 4.0 centres in Europe. Second, we identify the potentials of all EU regions to become the future Industry 4.0 centers of knowledge in Europe. The same patent data are used to identify I4T-related technologies, i.e. technologies that are frequently recombined with I4T based on co-occurrences of patent claims. This analysis enables us to draw the I4-knowledge space, a visual representation of the relatedness between I4Ts and other technological fields. Third, we use this I4-knowledge space to estimate the impact of relatedness on the entry of I4Ts in EU regions. This helps to understand to what extent the current knowledge bases of regions impact their likelihood to become I4T leaders. Fourth, we map future diversification opportunities in I4Ts for EU regions.

Section 2 gives a brief overview of the literature on Industry 4.0 Technologies. Section 3 connects the principle of relatedness to I4T potentials of regions. Here, we provide an analytical framework based on the principle of relatedness to identify the potential of regions to diversify into I4Ts. Section 4 will construct and present the I4-knowledge space as a network representation of the relatedness between I4Ts and other technologies. Section 5 will present a regional diversification model in Europe that estimates the impact of relatedness on the entry of I4Ts in EU regions. Section 6 will map the future Industry 4.0 centers of knowledge production in Europe. Section 7 concludes.

2. INDUSTRY 4.0 TECHNOLOGIES

New digital technologies around the Internet of Things, robotics, artificial intelligence and self-driving cars are expected to have a pervasive effect on a wide range of sectors of the economy (Liao et al. 2017; Lu 2017). Scholars tend to refer to those as Industry 4.0 technologies and sometimes even speak of a Fourth Industrial Revolution. According to Ménière et al. (2017), the Fourth Industrial Revolution is different from previous ones. While previous Industrial Revolutions have been associated with the increasing automation of repetitive physical work, I4T's are about the large-scale automation of entire groups of tasks, including repetitive intellectual or non-routine tasks. In the last couple of years, studies make an attempt to assess the possible negative consequences of automation for jobs and workers, especially in terms of the number and types of jobs and the particular work tasks that are expected to be displaced or under threat (Frey and Osborne 2016; Bessen et al. 2019).

I4T's are defined in different ways: there exists no consensus on what I4T stands for, and there is no formal classification of I4T activities. For Ménière et al. (2017), I4T stands for the massive deployment of the Internet of Things, in which objects that possess computing capabilities and are connected to a data network operate autonomously, based on own data collection or through data exchange with other objects. The Internet of Things stands for the network formed by objects that have "... the autonomy to decide how to act or react, based on information that they have collected or received from other devices" (p. 20). Ménière et al. (2017) distinguish between three sectors in which I4T's are found: (1) core technologies (hardware, software, connectivity); (2) enabling technologies (analytics, security, artificial intelligence, position determination, power supply, 3D systems, user interfaces); and (3) application domains (home, personal, enterprise, manufacturing, infrastructure, vehicles). Ciffolilli and Muscio (2018) use a more narrow definition, in which I4T is connected to smart factories in which new digital and other technologies change the organization of value chains. Their focus is on the 'digitilisation' of manufacturing that gets integrated with new ICT's. This conceptualization of I4T echoes a strong desire of national governments to boost reindustrialization (Santos et al. 2017).

The first I4T's emerged some decades ago, but there are signs that I4T's have been taking off in the last decade. Major established companies in the world turn out to be very active in the development of I4T's. Ménière et al. (2017) estimated that only 25 global ICT companies, many of them in Asia, the US and Europe, take about half of all I4T patent applications, especially in core technologies. Based on the

location of patent applications, Ménière et al. (2017) identify top EU regions in I4T. These top I4T regions (like Île-de-France and Upper Bavaria) are more or less the same as the ones that dominated the list of top EU regions of the Third Revolution. This may be attributed to the fact that large established ICT companies from the Third Revolution also stand out as the champions of I4T.

Ciffolilli and Muscio (2018) investigated the Seventh Framework Programs of the EU to identify the development of enabling technologies linked to Industry 4.0. They classified I4T's on the basis of a taxonomy of key research areas based on expert peer reviews. According to Ciffolilli and Muscio (2018), “the main enabling technologies of Industry 4.0 are: (1) Advanced Manufacturing Solutions – Interconnected, easily programmable collaborative robots; (2) Additive Manufacturing – such as 3D printers connected to digital development software; (3) Augmented Reality – Augmented reality supporting production processes; (4) Simulation – Simulation between interconnected machines to optimise processes; (5) Horizontal/Vertical Integration – Integration of information along the value chain, from suppliers to consumers; (6) Industrial Internet & Cloud – Multidirectional communication between production processes and products; management of big data on open systems; (7) Cyber-security – Security in network operations and on open systems; and (8) Big Data and Analytics – Big data analysis to optimise products and processes” (p. 2331). Using Wikipedia data, Chiarello et al. (2018) identified and mapped a total of eight clusters of Industry 4.0 technologies.

Moreover, Ciffolilli and Muscio (2018) examined the geography of participation in Industry 4.0 collaborative research projects for 294 NUTS 2 regions. So, their focus was on input of research, rather than output, as reflected in patents, publications or productivity. They showed the geography of I4T research is highly uneven in the EU: it is highly concentrated in South Germany (Baden-Württemberg and Bavaria), North Rhine–Westphalia, Rhône-Alpes, Île-de-France, and the Italian region of Lombardia, while Eastern and Southern Europe participate only to a limited extent.

3. THE PRINCIPLE OF RELATEDNESS AND I4T POTENTIAL OF REGIONS

In order to assess the potential of European regions to develop and participate in the production of new knowledge and technologies associated with the Fourth Industrial Revolution, we need to understand how regions diversify in new technologies in the first place. In the last decade, there has been a vast empirical literature that has focused on exactly that question, which we refer to as the regional diversification literature (Boschma 2017), and which builds on the principle of relatedness (Hidalgo et al. 2018). The regional diversification literature claims that regions are more likely to develop new activities related to their existing activities. New capabilities required for related diversification (like new knowledge, skills, networks, institutions) are easier to acquire when closer to existing capabilities in the region. This stands in contrast to unrelated diversification in which the development of completely new activities requires radical transformation of existing local capabilities (Neffke et al. 2018). This implies unrelated diversification is accompanied by high risks of failure and huge transformation costs,

and thus more unlikely to happen. The more radical the transformation in the underlying local capabilities is required, the more it concerns unrelated diversification

There are different ways of assessing the complementarities or relatedness between activities (Boschma et al. 2013; Freire 2017). Activities are considered related when they demand similar requirements or capabilities (Teece et al. 1994). Large datasets on trade or labour mobility are used to determine which activities require similar capabilities (Neffke and Henning 2013). Hidalgo et al. (2007) developed the product space concept to identify the relatedness between (export) products. They employed co-occurrence analysis of products in the export portfolios of countries. When countries are specialized in the same products, these products are considered demanding similar capabilities (Hausmann and Klinger 2007). Using that information, they construct a network, in which a node stands for a product, and a link between nodes identifies the level of relatedness between two products. This network projection of the product space shows which products are centrally positioned in the network, meaning they are related with many other products (and thus having capabilities in common), and which products are isolates (not sharing similar capabilities with other products).

After having determined the degree of relatedness between activities, the regional diversification literature tests whether relatedness is a crucial driver behind diversification in regions. The main idea is that regional capabilities condition which new activities will be feasible to develop in regions, and which ones will not. A region has a higher probability to develop new products when these are related to existing products in a region. This idea has been replicated by numerous studies (Boschma 2017). Neffke et al. (2011) found that an industry is more likely to enter a region when technologically related to pre-existing industries in that region. Similar findings have been reported for NUTS-2 regions in the EU (Cortinovis et al. 2017), and for prefectures in China (Guo and He 2017; He et al. 2018).

Scholars have also used patent data to investigate the diversification process in regions. Rigby (2015) and Boschma et al. (2015) used measures of relatedness between patent classes to describe the rise of new technologies in U.S. cities. Using patent data, they construct a technology space to determine relatedness between technologies that is based either on co-occurrence of technology classes on a patent document, or on citations across technology classes. Studies find that technologies related to pre-existing technologies had a higher probability to enter metropolitan regions in the US (Kogler et al. 2013; Rigby 2015; Boschma et al. 2015) and NUTS-2 regions in the EU (Balland et al. 2018a).

So, there is strong support for the thesis that new activities do not start from scratch. Unrelated diversification is a rare event, because it requires a drastic transformation of local capabilities. New activities in region are often related to existing local activities, providing capabilities from which new activities draw resources. This has been investigated for a broad range of new activities like industries, products, jobs and technologies (Boschma 2017), but also for particular types of activities, such as the emergence of eco-technologies (Van den Berge and Weterings 2014; Montresor and Quatraro 2018; Corradini 2019; Santoalha and Boschma 2019), fuel cell technology (Tanner 2016), nano-technologies (Colombelli et al. 2014) and bio-technologies (Boschma et al. 2014). Without exception, these studies confirm the importance of the principle of relatedness (Hidalgo et al. 2018).

In this paper, we will use this principle of relatedness to identify potentials of regions to diversify and participate in I4T. First, we examine whether the ability of EU regions to develop new technologies associated with I4T is depending on capabilities related to their existing technological specializations. We investigate how revolutionary the Fourth Industrial Revolution is from a geographical point of view, by testing whether I4T's develop from scratch in regions, and to what extent they build on existing local capabilities. Second, we use the same relatedness framework to identify the future potentials of EU regions to develop I4T, by looking at the extent to which they possess the required capabilities to do so.

4. MAPPING THE I4-KNOWLEDGE SPACE

To map the geography of I4 knowledge production in Europe, we need to (1) identify precisely the I4 technological domains, (2) be able to geo-locate the regions where they are being developed, and (3) measure how they connect to other knowledge bases (relatedness). In this report, we will use patent applications to the European Patent Office (EPO) and network-based relatedness metrics.

We use the OECD-REGPAT database (edition March 2018) to identify I4T patents and compute measures of relatedness. OECD-REGPAT is a regionalized patent dataset that derives from PATSTAT (Maraut, Dernis, Webb, Spiezia and Guellec 2008). It contains patent applications to the European Patent Office (EPO) from 1977 to 2017. Patent applications are regionalized at the NUTS2 level by inventor addresses. We supplement this data with Cambridge Econometrics to construct control variables, such as population density and GDP per capita.

To be included in the analysis, I4 technologies have to satisfy two criteria. First, they have been identified in Section 2 as key technologies associated with the 4th Industrial Revolution. Second, they have to connect directly or indirectly to the Cooperative Patent Classification (CPC). The CPC is one of the most precise technological classifications in the world, breaking down technologies in approximately 250,000 categories. For some I4Ts, this is straightforward to do, such as Cloud Computing, because all patents that make an invention claim to the technology of grid computing is classified under the category G06F9/5072. For other I4Ts, we are able to reconstruct them indirectly by combining sub-categories, like for the category of Autonomous Vehicles that combines sub-categories such as cruise control (B60W30/14) and the lidar system (G01S17) which are key components of autonomous vehicles technologies. However, these categories do not enable us to identify accurately all dimensions of I4Ts, such as the Internet of Things (IoT) or blockchain technologies. To identify patents in these technologies, one would have to develop heuristics and mine patent abstracts and full-texts. Attempts have been made to apply deep learning for this purpose, but there is no consensus at the moment.

We identified nine I4Ts that are listed in Table 1: (1) additive manufacturing; (2) artificial intelligence; (3) augmented reality; (4) autonomous robots; (5) autonomous vehicles; (6) cloud computing; (7) cybersecurity; (8) quantum computers; and (9) system integration. Table 1 shows the number of patents at EPO in each of the 9 categories for the period 2002-2016. Patenting in Cybersecurity is the most

intense by far. Patenting in I4T is gradually increasing over time. Most categories witness an increase in number of patents, with the exception of Cybersecurity and (in particular) Quantum Computers.

Table 1. I4T patent count per period

I4T	patents (2002-2006)	patents (2007-2011)	patents (2012-2016)
Additive manufacturing	823	1,040	1,739
Artificial intelligence	483	828	1,321
Augmented reality	992	1,673	2,545
Autonomous robots	745	970	1,154
Autonomous vehicles	1,979	2,457	3,099
Cloud computing	65	97	224
Cybersecurity	11,501	11,513	10,237
Quantum computers	2,294	1,255	266
System integration	538	2,007	1,326
Total	19,420	21,840	21,911

To map the current and future geography of I4T, it is not enough to flag I4T patents and geo-locate them. Our framework is based on the idea presented in Section 2 that I4 technologies will only thrive if they connect to an eco-system of related technologies that will nurture their growth by drawing on the specific knowledge bases in regions (Boschma 2017; Balland et al. 2018a; Hidalgo et al. 2018).

First of all, this requires a measure of relatedness between technologies. To measure technological relatedness between patent classes, we use the distribution of knowledge claims by CPC class on each patent application to the EPO, following Boschma et al. (2015) and Rigby (2015). This is done by counting the number of EU patents for a given period that contains a co-class pair, say i and j , and then standardizing this count by the total number of patents that record knowledge claims in I4T/CPC classes i and j . Relatedness is, therefore, a standardized measure of the frequency with which two I4T/CPC classes appear on the same patent. We use a standardization method (Steijn 2017) based on Van Eck and Waltman (2009), as implemented in the relatedness function of the EconGeo R package (Balland 2017). Once we have calculated relatedness between technologies, we can formalize relatedness between technologies as a network, the so-called ‘knowledge space’. The knowledge space is an $n \times n$ network where the individual nodes i ($i = 1, \dots, n$) represent technological categories (I4T or CPC classes), and the links between them indicate their degree of relatedness. We compute relatedness between each pair of technologies i and j for three different non-overlapping periods: 2002-2006, 2007-2011, 2012-2016.

Figure 1 is a graph visualization of the knowledge space for the third period. I4Ts tend to locate at the periphery of this network, signaling that they build on capabilities that are not generic, and not easy to

find in other technologies. It also shows that most I4Ts tend to cluster around similar technologies, but some I4Ts are more isolated from other I4Ts like Additive Manufacturing. We notice in particular a group around computer-related technologies, and another one around autonomous technologies.

Figure 1. The position of I4Ts in the Knowledge Space 2012-2016

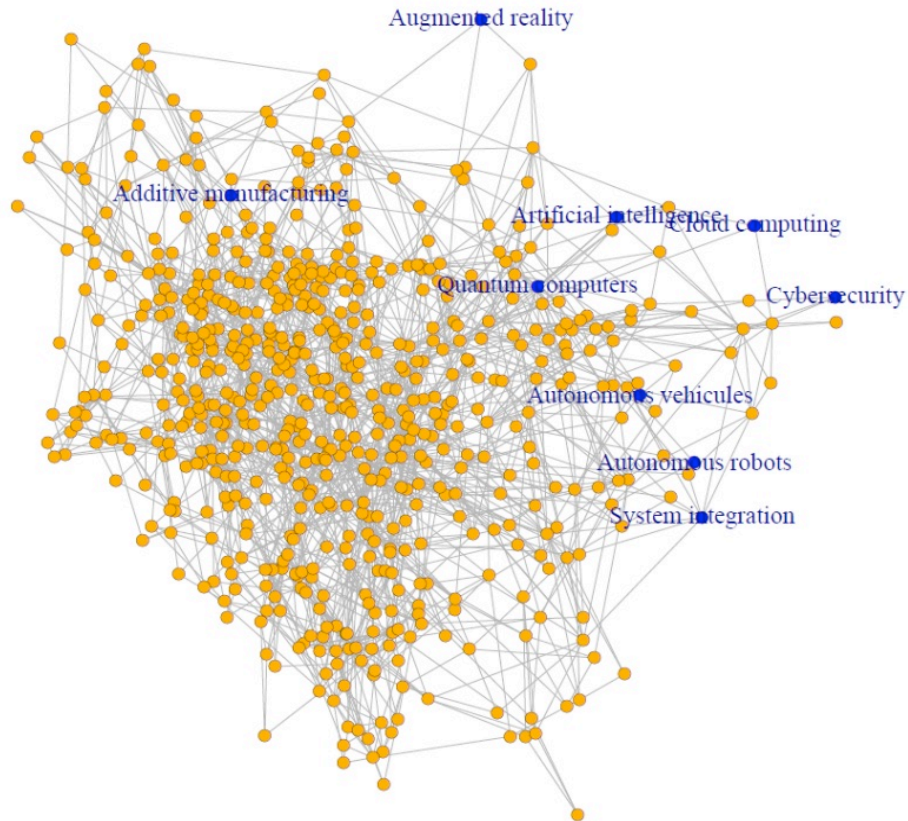
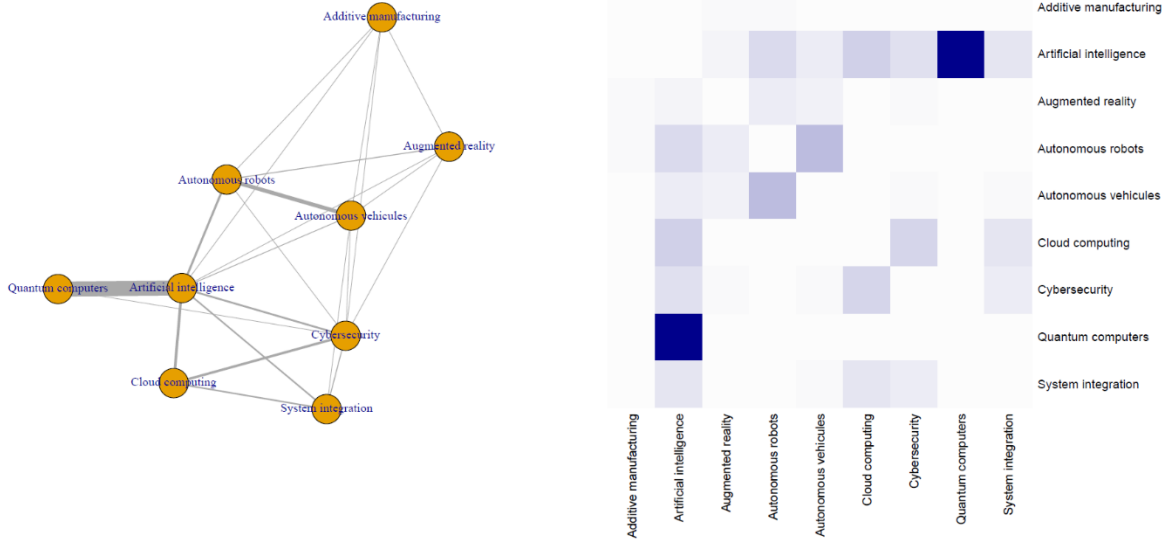


Figure 2 explores relatedness between I4Ts more in detail. On the left-hand side, relatedness is displayed as a network (as in Figure 1), while on the right-hand side relatedness is displayed as a heatmap, with more blue-intense colors meaning a stronger level of relatedness. The strongest levels of relatedness appear to be between Quantum Computers and AI, and between Autonomous Robots and Autonomous Vehicles. There is a strong knowledge cluster around computer-related I4T (Quantum Computers, AI, Cloud Computing, and Cybersecurity, System Integration), and a second one around Autonomous Robots/Vehicles. AI seems to link these two clusters. Augmented Reality and Additive Manufacturing, in particular, appear to be more disconnected from the other I4Ts.

Figure 2. Relatedness between I4Ts



5. MODELING THE ENTRY OF I4Ts IN EU REGIONS

While Figures 1-2 display the relatedness between technology pairings, we will now identify the knowledge structure of individual regions within the EU. We include all EU28 regions plus regions from Norway and Switzerland. We are particularly interested in exploring the knowledge cores of regions, or how much of the technology produced within each NUTS2 region (as captured by the number of patents) tends to cluster around I4T, which would signal a strong local environment for their growth.

For each region r , we calculated the density of technology production in the vicinity of I4T i . Following Hidalgo et al. (2007) and Balland et al. (2018a), the density of knowledge production around a given I4T i in region r at time t is derived from the technological relatedness $\varphi_{i,j,t}$ of technology i to all other technologies j (I4T and non-I4T) in which the region has a relative technological advantage (RTA), divided by the sum of technological relatedness of technology i to all the other technologies j in the reference region at time t :

$$\text{RELATEDNESS_DENSITY}_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100$$

RTA is a binary variable that takes value 1 when a region has a greater share of patents in technology class i than the reference region (all EU regions), and takes the value of 0 otherwise. A region r has RTA in the production of technological knowledge i ($r = 1, \dots, n; i = 1, \dots, k$) such that $RTA_{r,i,t} = 1$ if:

$$\frac{patents_{r,i}^t / \sum_i patents_{r,i}^t}{\sum_r patents_{r,i}^t / \sum_r \sum_i patents_{r,i}^t} > 1$$

The higher the region's score on relatedness density, the closer, on average, its existing set of technologies to I4T. In other words, relatedness density reflects an overall average score of the potential of a region to develop a specific I4T.

We estimated the probability that a region develops a new Relative Technological Advantage (RTA) in a I4T. Following the principle of relatedness (Hidalgo et al., 2018) and the methodology outlined by Boschma et al. (2015) and Balland et al. (2018a), our main variable of interest is the relatedness density between a I4T and the overall technological portfolio of a region. We also include two control variables at the regional level, that is, population (log) and GDP per capita, because they may affect the entry probability of an I4T in a region. Table 2 provides summary statistics for the variables.

Table 2. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Period	5,220	2.500	0.500	2	3
Entry	4,308	0.127	0.333	0.000	1.000
Relatedness density	5,220	17.950	24.574	0.000	99.980
GDP per capita (k)	4,383	23.524	9.534	5.000	93.380
Population	4,509	1,888,205.000	1,503,705.000	26,381.600	11,725,090.000

All specifications are estimated at the region-technology-period level. We use a linear probability model (LPM) to assess the probability that a region specializes in a new I4T (entry) using the following specification:

$$ENTRY_{r,i,t} = \beta_1 RELATEDNESS_DENSITY_{r,i,t-1} + \beta_2 REGIONS_{r,t-1} + \varphi_i + \alpha_t + \varepsilon_{r,i,t}$$

If a region already has a RTA in I4T i in $t-1$, then the observation is removed from the analysis, because the respective I4T i cannot enter by definition. If the region does not already have a RTA in I4T i in $t-1$

but it does in t , then $\text{entry}_{r,i,t} = 1$ (and $\text{entry}_{r,i,t} = 0$ otherwise). Following the literature on regional diversification, we expect a positive coefficient for relatedness density. The baseline specification is a two-way fixed-effects model where φ_i is a I4T fixed effect, α_t is a time fixed effect, and $\varepsilon_{r,i,t}$ is a regression residual. Our panel consists of data for 290 NUTS2 regions and nine I4T's over the period 2002-2016. We average the data over non-overlapping five-year periods, denoted by t . To dampen potential endogeneity issues, all the independent variables are lagged by one period, denoted by $t-1$.

In all entry models in Table 3, we find that relatedness density has a positive and significant effect on the probability that a region specializes ($\text{RTA} > 1$) in a new I4T, which is expected and consistent with other findings (Boschma et al. 2015; Rigby 2015; Balland et al. 2018a). The effect of relatedness is also strong: an increase of 10% in relatedness density in a region is associated with a 52 to 63% relative increase in the entry probability of a given I4T in a region¹. We also find that regions with a higher GDP/capita and a larger population base are more likely to enter in I4T. This is consistent with findings that more complex technologies (such as I4T) disproportionately concentrate in large cities (Balland and Rigby 2017; Balland et al. 2018b).

Table 3. Diversification model (Industry 4.0 technologies)

	<i>Dependent variable:</i>		
		I4-tech entry	
	(1)	(2)	(3)
Relatedness density	0.008*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
GDP per capita		0.002** (0.001)	0.002** (0.001)
Population (log)		0.027*** (0.007)	0.026*** (0.007)
Artificial intelligence			0.068*** (0.025)
Augmented reality			0.046* (0.024)
Autonomous robots			0.066*** (0.024)
Autonomous vehicles			0.049** (0.025)

¹ The mean of entry is 0.12. In model 1, for instance, the probability of entry increases (in absolute terms) by about 0.008 for any additional unit of relatedness density (scale 0 to 100). Therefore, an additional 10 points in relatedness density boosts entry by about $(10 \times 0.008) / 0.126 = 63\%$ (relative increase).

Cloud computing			0.026 (0.026)
Cybersecurity			-0.008 (0.024)
Quantum computers			-0.007 (0.024)
System integration			0.017 (0.024)
Time (period 3)			-0.019 (0.012)
Constant	0.063*** (0.007)	-0.342*** (0.107)	-0.358*** (0.109)
Observations	4,308	3,485	3,485
R ²	0.043	0.042	0.049
Adjusted R ²	0.043	0.041	0.046
Residual Std. Error	0.326 (df = 4306)	0.332 (df = 3481)	0.331 (df = 3472)
F Statistic	193.431*** (df = 1; 4306)	50.364*** (df = 3; 3481)	14.944*** (df = 12; 3472)

* ** *** p<0.01

6. MAPPING THE FUTURE INDUSTRY 4.0 CENTER OF KNOWLEDGE PRODUCTION

Based on the knowledge space and diversification model, we map the potential for future diversification opportunities in I4Ts for all EU regions. In Table 4, we present the top 20 regions that have the fittest technological ecosystem and highest potential to develop I4Ts on average. In Table 5, we decompose these results for each of the nine I4Ts: Artificial Intelligence, System Integration, Additive Manufacturing, Artificial Intelligence, Augmented Reality, Autonomous Robots, Autonomous Vehicles, Cloud Computing, Cybersecurity and Quantum Computers.

Table 4. Top 20 EU regions: relatedness density around all I4Ts*

I4Ts	
Oberbayern [DE]	72,7
Île-de-France [FR]	66,7
Outer London [UK]	55,2
Länsi-Suomi [FI]	52,0
Berlin [DE]	51,7
Östra Mellansverige [SE]	49,6
Wien [AT]	49,2

Inner London [UK]	49,0
Comunidad de Madrid [ES]	48,3
Bretagne [FR]	46,9
Praha [CZ]	44,7
Małopolskie [PL]	44,6
Śląskie [PL]	44,1
Prov. Antwerpen [BE]	43,7
Surrey, East and West Sussex [UK]	43,3
Stuttgart [DE]	42,5
Mittelfranken [DE]	41,8
Provence-Alpes-Cote d'Azur [FR]	41,7
Chemnitz [DE]	41,6
<i>Note: excluding 'cloud computing' and 'quantum computers'</i>	

Table 5. Top 20 EU regions: relatedness density around each I4T

Artificial Intelligence		System Integration		Additive Manufacturing	
Île-de-France [FR]	88,6	Rhône-Alpes [FR]	83,2	Oberbayern [DE]	72,6
Comunidad de Madrid [ES]	88,2	Mittelfranken [DE]	82,8	Unterfranken [DE]	71,9
South. and East. [IE]	87,8	Liguria [IT]	82,0	Zürich [CH]	71,5
Berlin [DE]	87,4	Wien [AT]	80,0	Schleswig-Holstein [DE]	67,2
Inner London [UK]	87,0	Herefordshire, Worcestershire and Warwickshire [UK]	80,0	Bremen [DE]	67,2
Wien [AT]	85,8	Stuttgart [DE]	78,8	Düsseldorf [DE]	67,1
Trøndelag [NO]	85,3	Kassel [DE]	75,5	Veneto [IT]	65,8
Oberbayern [DE]	84,1	Östra Mellansverige [SE]	74,6	Schwaben [DE]	65,7
Provence-Alpes-Côte d'Azur [FR]	84,1	Île-de-France [FR]	73,5	Chemnitz [DE]	65,3
Surrey, East and West Sussex [UK]	83,8	PaÃs Vasco [ES]	73,0	Lüneburg [DE]	64,6
East Anglia [UK]	83,8	Berlin [DE]	72,9	Cheshire [UK]	64,0
Outer London [UK]	83,4	Arnsberg [DE]	72,3	Ostschweiz [CH]	61,6
Helsinki-Uusimaa [FI]	83,0	Nordjylland [DK]	71,9	South Yorkshire [UK]	61,3
Hampshire and Isle of Wight [UK]	82,6	Detmold [DE]	70,8	Auvergne [FR]	61,0
Rhône-Alpes [FR]	82,2	Oberpfalz [DE]	70,7	Derbyshire and Nottinghamshire [UK]	60,0
Bretagne [FR]	82,2	Karlsruhe [DE]	70,5	Trier [DE]	57,3
Praha [CZ]	82,0	Midtjylland [DK]	70,4	Västsvrige [SE]	55,9
Devon [UK]	81,9	Ticino [CH]	69,4	Provincia Autonoma di Bolzano/Bozen [IT]	55,8
Berkshire, Buckinghamshire, and Oxfordshire [UK]	81,4	Vorarlberg [AT]	68,9	Oberfranken [DE]	55,7

Région lémanique [CH]	80,9	Eastern Scotland [UK]	68,8	Lincolnshire [UK]	55,6
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Augmented Reality		Autonomous Vehicles		Autonomous Robots	
Île-de-France [FR]	72,6	Oberbayern [DE]	73,5	Schwaben [DE]	89,2
Thüringen [DE]	70,7	Tubingen [DE]	73,2	Pays de la Loire [FR]	87,0
Surrey, E.W.S[UK]	64,1	Schwaben [DE]	71,6	PaÃs Vasco [ES]	86,7
Bretagne [FR]	64,1	Östra Mellansverige [SE]	68,1	Oberbayern [DE]	85,6
Inner London [UK]	63,1	Stuttgart [DE]	66,5	Piemonte [IT]	85,3
Yugozapaden [BG]	62,7	Småland med öarna [SE]	65,8	Småland med öarna [SE]	82,7
Länsi-Suomi [FI]	62,1	Île-de-France [FR]	65,3	Slaskie [PL]	82,5
Noord-Brabant [NL]	61,7	Hannover [DE]	64,3	Stuttgart [DE]	80,8
Kärnten [AT]	61,5	Freiburg [DE]	63,7	Toscana [IT]	80,5
Wien [AT]	61,3	Västsvrige [SE]	62,8	Freiburg [DE]	79,1
Hannover [DE]	60,9	Liguria [IT]	61,7	Karlsruhe [DE]	78,6
Cataluña [ES]	60,8	Karlsruhe [DE]	60,4	Östra Mellansverige [SE]	78,3
Outer London [UK]	60,6	West Midlands [UK]	60,0	Agder og Rogaland [NO]	77,3
Eastern Scotland [UK]	59,5	Poitou-Charentes [FR]	59,6	Oberpfalz [DE]	76,4
Sydsverige [SE]	59,3	Provence-Alpes-Côte d'Azur [FR]	59,3	Provincia Autonoma di Trento [IT]	76,4
StÅ™ednÃ Āechy [CZ]	58,1	Midi-Pyrénées [FR]	58,9	Lüneburg [DE]	75,6
Wielkopolskie [PL]	57,0	Gloucestershire, Wiltshire and Bristol/Bath area [UK]	58,0	Chemnitz [DE]	75,6
Bedfordshire and Hertfordshire [UK]	56,8	Braunschweig [DE]	57,0	Lancashire [UK]	75,6
Å%szak-AlfÅ¶ld [HU]	56,7	Essex [UK]	56,9	Oberösterreich [AT]	74,6
Slaskie [PL]	56,4	Comunidad de Madrid [ES]	56,3	Île-de-France [FR]	74,1

Cloud Computing		Cybersecurity		Quantum Computers	
Helsinki-Uusimaa [FI]	99,6	Surrey, East and West Sussex [UK]	83,2	Rhône-Alpes [FR]	90,2
Inner London [UK]	99,6	Provence-Alpes-Côte d'Azur [FR]	81,4	Berlin [DE]	85,9
Outer London [UK]	99,5	Bretagne [FR]	79,3	East Anglia [UK]	84,0
Közép-Magyarország [HU]	99,4	Outer London [UK]	77,3	Aquitaine [FR]	83,9
Berkshire, Buckinghamshire, and Oxfordshire [UK]	99,2	Helsinki-Uusimaa [FI]	76,5	Dresden [DE]	83,9
Southern and Eastern [IE]	99,2	Comunidad de Madrid [ES]	72,8	Zuid-Holland [NL]	83,3
Basse-Normandie [FR]	98,9	Île-de-France [FR]	70,8	Southern and Eastern [IE]	82,9
Praha [CZ]	98,8	Länsi-Suomi [FI]	70,3	Île-de-France [FR]	82,0
Hampshire and Isle of Wight [UK]	98,5	Hampshire and Isle of Wight [UK]	69,4	Comunidad de Madrid [ES]	80,8
Oberbayern [DE]	98,2	Oberbayern [DE]	69,0	Inner London [UK]	80,6
Pomorskie [PL]	98,2	Közép-Magyarország [HU]	66,9	Hovedstaden [DK]	79,2
Stockholm [SE]	98,0	Oslo og Akershus [NO]	66,6	Sydsverige [SE]	76,8
Wien [AT]	98,0	Stockholm [SE]	65,8	Cornwall and Isles of Scilly	76,7

				[UK]	
Dél-Dunántúl [HU]	97,8	Région lémanique [CH]	64,6	Midi-Pyrénées [FR]	76,6
Border, Midland and Western [IE]	97,7	Southern and Eastern [IE]	61,7	Limousin [FR]	76,0
Groningen [NL]	97,7	Eesti [EE]	61,4	TÄ¼bingen [DE]	74,2
Lódzkie [PL]	97,6	Inner London [UK]	61,3	Unterfranken [DE]	73,3
Zürich [CH]:	97,4	Noord-Brabant [NL]	58,2	Thüringen [DE]	72,2
Brandenburg [DE]	97,4	Pohjois- ja Itä-Suomi [FI]	57,0	Tees Valley and Durham [UK]	71,8
Noord-Holland [NL]	97,4	Basse-Normandie [FR]	55,3	Hampshire and Isle of Wight [UK]	71,8

Note: Relatedness density is computed for the period 2012-2016. The relatedness figures for cloud computing and quantum computers should be interpreted with care, given the low levels of patenting activity during this period.

There are huge differences across EU regions with respect to their potential future participation in I4T. As shown in Table 4, the EU regions with the highest potential in I4T are Oberbayern (Munich), Île-de-France (Paris) and Outer London. Although 3 European countries (Germany, France and the UK) take up more than half of all top 20 EU regions in I4T, it is also noticeable that this top 20 regions is spread over 10 different European countries. As shown in Table 5, there are also significant differences across I4Ts regarding the leading regions in the EU. Broadly speaking, German regions like Oberbayern and Stuttgart tend to dominate and show high potentials in System Integration, Additive Manufacturing, Autonomous Robots and Autonomous Vehicles. UK regions tend to score high on Augmented Reality. Potential in Artificial Intelligence is high in UK regions, but also fairly distributed across other European countries, often found in their capital city regions, like Île-de-France and Comunidad de Madrid. High potentials in Cybersecurity are found in regions in France, UK and Finland in particular. At the same time, many EU countries are rarely mentioned, or not mentioned at all in these top 20 rankings, suggesting a weak technological potential to develop I4Ts in the near future.

7. CONCLUSIONS

This paper aimed to identify the future Industry 4.0 centers of knowledge production in Europe. A brief outline of the I4T literature learned there is no consensus on what I4T stands for. There also exists no formal classification of I4T activities. Based on patent data from the OECD-REGPAT database, we identified nine categories of I4Ts: (1) additive manufacturing; (2) artificial intelligence; (3) augmented reality; (4) autonomous robots; (5) autonomous vehicles; (6) cloud computing; (7) cybersecurity; (8) quantum computers; and (9) system integration.

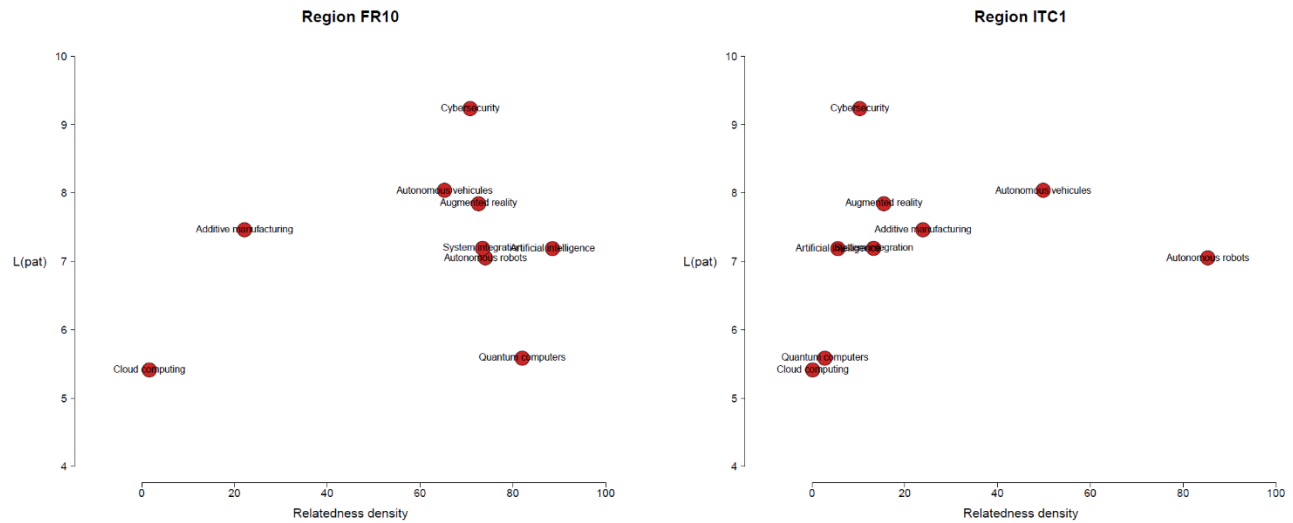
Building on recent insights from the regional diversification literature, we expected I4Ts to thrive in regions where they can draw resources from related technologies available at the regional scale. Using the knowledge space concept, we identified I4T-related technologies, i.e. technologies that are frequently combined with I4Ts based on the co-occurrences of technologies in patent documents. This

resulted in the construction of an Industry 4.0 knowledge space, a visual representation of the level of relatedness between I4Ts and other technological fields. We found that I4Ts are located at the periphery of the knowledge space. Most I4Ts tend to cluster around similar technologies. In particular, we could observe a cluster around computer-related Industry 4.0 technologies, and another one centered on autonomous-related I4 technologies. Artificial Intelligence tends to link both I4T clusters.

We used this I4-knowledge space to estimate the impact of relatedness on the entry of I4Ts in EU regions during the period 2002-2016. As expected, we found that relatedness has a strong and positive effect on the probability that a region specializes in a new I4T. This shows that regions with a high potential in terms of I4T-related technologies are more likely to diversify successfully in new I4Ts. We also found that regions with a higher GDP/capita and with a larger population are more likely to enter I4T. When we map the future Industry 4.0 centers of knowledge production in the EU for all nine I4Ts, we found huge differences across EU regions: German, French and UK regions tend to show a high potential to develop I4Ts, but we also found significant differences across the nine I4Ts. German regions show high development potential in System Integration, Additive Manufacturing, Autonomous Robots and Autonomous Vehicles, while UK regions have strong I4 potential in Augmented Reality. Potential in Artificial Intelligence is high in UK regions and many capital city regions in the EU. We also found that many EU countries and regions have a weak potential to develop I4Ts in the near future.

Our findings imply that public policy intervention that aims to develop Industry 4.0 should take as point of departure the particular I4 potentials that region possess. Regions with a low I4T potential should not invest public funds in I4T because the risk of failure is too high. Public policy should target those regions that have related I4T capabilities, as these provide local assets that might be exploited to make policy effective. This is further illustrated in Figure 3 that maps development opportunities in all nine I4Ts in the French region Ile de France and the Italian region Piemonte. Relatedness density is shown on the X-axis, while the Y-axis indicates the number of patents (log) in each I4T in the whole of Europe (so the latter does not vary across regions). What can be observed is that Ile de France has a low I4T potential (low relatedness density) in Cloud Computing and Additive Manufacturing, but it has high potential in the other seven I4Ts. The case of Piemonte tells a very different story: this region has high I4T potential in Autonomous Robots and Autonomous Vehicles, which partly reflects its techno-industrial past, but Piemonte has very low potential in other I4Ts. This illustration shows how important it is to develop an I4T policy that defies a ‘one-size-fits-all’ framework, but instead is tailor-made and targets I4-related capabilities in order to increase the probability of successful policy intervention.

Figure 3. Mapping I4T opportunities of Ile de France (FR10) and Piemonte (ITC1)



References

Balland, P.A. (2017) EconGeo: Computing Key Indicators of the Spatial Distribution of Economic Activities, R package version 1.3: <https://github.com/PABalland/EconGeo>.

Balland, P.A. and Rigby, D. (2017) The Geography of Complex Knowledge, *Economic Geography*, 93 (1): 1-23.

Balland, P.A., Boschma, R., Crespo, J. and Rigby, D. (2018a) Smart Specialization policy in the EU: Relatedness, Knowledge Complexity and Regional Diversification, *Regional Studies*, forthcoming, doi: 10.1080/00343404.2018.1437900.

Balland, P.A., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., and Hidalgo, C. (2018b) Complex Economic Activities Concentrate in Large Cities, *Papers in Evolutionary Economic Geography*, 18 (29): 1-10.

Berge, M. van den, and A. Weterings (2014) Relatedness in eco-technological development in European regions, The Hague: Planbureau voor Leefomgeving.

Bessen, J., M. Goos, A. Salomons and W. van den Berge (2019) Automatic reaction - what happens to workers at firms that automate?, *CPB Discussion Paper*, Netherlands Bureau for Economic Policy Analysis, The Hague.

Boschma, R. (2017) Relatedness as driver behind regional diversification: a research agenda, *Regional Studies*, 51 (3), 351-364.

- Boschma, R., P.A. Balland and D.F. Kogler (2015) Relatedness and technological change in cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010, *Industrial and Corporate Change*, 24 (1), 223-250.
- Boschma, R., G. Heimeriks and P.A. Balland (2014) Scientific knowledge dynamics and relatedness in biotech cities, *Research Policy* 43 (1), 107-114.
- Boschma, R., A. Minondo and M. Navarro (2013) The emergence of new industries at the regional level in Spain. A proximity approach based on product-relatedness, *Economic Geography* 89 (1), 29-51.
- Chiarello, F., L. Trivelli, A. Bonaccorsi and G. Fantoni (2018) Extracting and mapping industry 4.0 technologies using Wikipedia, *Computers in Industry* 100, 244-257.
- Ciffolilli, A. and A. Muscio (2018) Industry 4.0: national and regional comparative advantages in key enabling technologies, *European Planning Studies* 26 (12), 2323-2343.
- Colombelli, A., J. Krafft and F. Quatraro (2014) The emergence of new technology-based sectors in European regions: a proximity-based analysis of nanotechnology, *Research Policy* 43, 1681-1696.
- Corradini, C. (2019) Location determinants of green technological entry: evidence from European regions. *Small Business Economics* 52, 845-858.
- Cortinovis, N., J. Xiao, R. Boschma and F. van Oort (2017) Quality of government and social capital as drivers of regional diversification in Europe, *Journal of Economic Geography* 17 (6), 1179–1208.
- Freire, C. (2017) *Diversification and structural economic dynamics*, Maastricht: Boekenplan.
- Frey, C. B. and Osborne, M. (2016). The Future of Employment: How Susceptible are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114:254–280.
- Gress, D.R. and Kalafsky, R.V. (2015) Geographies of production in 3D: theoretical and research implications stemming from additive manufacturing, *Geoforum* 60, 43-52.
- Guo, Q. and C. He (2017) Production Space and Regional Industrial Evolution in China. *Geojournal* 82, 379-396.
- Hall, P. and P. Preston (1988) *The carrier wave. New information technology and the geography of innovation 1846-2003*, London: Unwin Hyman.
- Hausmann, R. and Klinger, B. (2007), The Structure of the Product Space and the Evolution of Comparative Advantage, *CID Working Paper* no. 146.
- He, C., Y. Yan and D. Rigby (2018), Regional Industrial Evolution in China. *Papers in Regional Science* 97 (2), 173-198.

Hidalgo, C., Balland, P.A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., and Zhu, S. (2018) The Principle of Relatedness, Proceedings of the 20th International Conference on Complex Systems.

Hidalgo, C.A., Klinger, B., Barabasi, A.L. and Hausmann, R. (2007) The product space and its consequences for economic growth, *Science* 317, 482–487.

Kogler, D.F., D.L. Rigby and I. Tucker (2013) Mapping Knowledge Space and Technological Relatedness in US Cities, *European Planning Studies* 21(9), 1374-1391.

Lecuyer, C. (2006) *Making Silicon Valley. Innovation and the growth of high tech, 1930-1970*, Cambridge: MIT Press.

Liao, Y., F. Deschamps, E. de Freitas Rocha Loures and L. Felipe Pierin Ramos (2017) Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal, *International Journal of Production Research* 55 (12), 3609-3629.

Lu, Y. (2017), Industry 4.0: A survey on technologies, applications and open research issues, *Journal of Industrial Information Integration* 6, June, 1-10.

Markusen, A., P. Hall and A. Glasmeier (1986) *High tech America: the what, how, where and why of the sun-rise industries*, Boston: Allen & Unwin.

Marshall, M. (1987) *Long waves of regional development*, London: MacMillan.

Ménière, Y., I. Rudyk and J. Valdes (2017), *Patents and the Fourth Industrial Revolution. The inventions behind digital transformation*, European Patent Office, Munich.

Montesor, S. and Quatraro, F. (2018), Green technologies and smart specialisation strategies: a European patent-based analysis of the intertwining of technological relatedness and Key-Enabling-Technologies, Department of Economics and Statistics Cognetti de Martiis. Working Papers 201808, University of Turin.

Muro, R. Maxim and J. Whiton (2019) Automation and artificial intelligence. How machines are affecting people and places, Metropolitan Policy Program, Brookings, Washington.

Neffke, F., M. Hartog, R. Boschma and M. Henning (2018) Agents of structural change. The role of firms and entrepreneurs in regional diversification, *Economic Geography* 94 (1), 23-48.

Neffke F. and Henning M. (2013) Skill-relatedness and firm diversification, *Strategic Management Journal* 34 (3), 297-316.

Neffke F., Henning M. and Boschma, R. (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions, *Economic Geography* 87(3), 237–265.

- Perez, C. and L. Soete (1988) Catching up in technology: entry barriers and windows of opportunity, in: G. Dosi, C. Freeman, R. Nelson, G. Silverberg and L. Soete (eds.) *Technical Change and Economic Theory*, London/New York: Pinter Publishers.
- Rigby, D. (2015) Technological relatedness and knowledge space. Entry and exit of US cities from patent classes, *Regional Studies* 49 (11), 1922-1937.
- Santoalha, A. and R. Boschma (2019) Diversifying in green technologies in European regions: does political support matter? Papers in Evolutionary Economic Geography, no. 19.22, Utrecht University, Utrecht.
- Santos, C., Mehraei, A., Barros, A. C., Araújo, M., & Ares, E. (2017). Towards Industry 4.0: An overview of European strategic roadmaps. *Procedia Manufacturing*, 13, 972–979.
- Scott, A. (1988) *New Industrial Spaces: Flexible Production Organization and Regional Development in North America and Western Europe*, London: Pion.
- Steijn, M.P.A. (2017) Improvement on the association strength: implementing probability measures based on combinations without repetition, Working Paper, Utrecht University.
- Strange, R. and A. Zucchella (2017) Industry 4.0, global value chains and international business, *Multinational Business Review* 25 (3), 174-184.
- Tanner, A.N. (2016) The emergence of new technology-based industries: the case of fuel cells and its technological relatedness to regional knowledge bases, *Journal of Economic Geography* 16 (3), 611-635.
- Teece, D. J., Rumelt, R., Dosi, G. and Winter, S. G. (1994): Understanding corporate coherence: theory and evidence. *Journal of Economic Behaviour Organisation*, 23, 1-30.
- Van Eck, N.J. and Waltman, L. (2009) How to normalize cooccurrence data? An analysis of some well-known similarity measures, *Journal of the American Society for Information Science and Technology* (8), 1635-1651.