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EU-funded investment in Artificial Intelligence and regional specialization[1]

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Abstract

Artificial Intelligence (AI) is seen as a disruptive and transformative technology with the potential to impact on all societal aspects, but particularly on competitiveness and growth. While its development and use has grown exponentially over the last decade, its uptake between and within countries is very heterogeneous. The paper assesses the geographical distribution at NUTS2-level of EU-funded investments related to AI during the programming period 2014-2020. It also examines the relationship between this specialization pattern and regional characteristics using a spatial autoregressive model. Such an analysis provides a first look at the geography of public investment in AI in Europe, which has never been done before.

Results show that in the period 2014-2020, around 8 billion EUR of EU funds were targeted for AI investments in the European regions. More developed regions have a higher specialization in AI EU-funded investments. This specialization also generates spillover effects that enhance similar specialization patterns in neighboring regions. AI-related investments are more concentrated in regions with a higher concentration of ICT activities and that are more innovative, highlighting the importance of agglomeration effects. Regions that have selected AI as an innovation priority for their Smart Specialization Strategies are also more likely to have a higher funding specialization in AI. Such findings are very relevant for policymakers as they show that AI-related investments are already highly spatially concentrated. This highlights the importance for less-developed regions to keep accessing to sufficient amounts of pre-allocated cohesion funds and to devote them for AI-related opportunities in the future.

JEL Classification: O31, R58, R12, O52

Keywords: Artificial intelligence; Public subsidy; Territorial specialization; Europe

Note: ***This article is sole responsibility of the authors and do not necessarily reflect the positions of GEE or the Portuguese Ministry of Economy*.**

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1. Introduction

Artificial Intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence (Aghion et al., 2017). It stands as a transformative force, marking a new milestone in the evolution of digital technologies. This disruptive technology has the potential to revolutionize all economic sectors across the world by improving efficiency (Brynjolfsson et al., 2021), driving innovation (Agrawal et al., 2023), new business opportunities (Xu et al., 2021), among others. The growth and uptake of AI has been exponential but not at the same pace all around the world (Maslej et al., 2023). In the global landscape, while the United States (US) is leading AI investment, the European Union (EU) is substantially lagging behind (Righi et al., 2020; Evas et al., 2022; Maslej et al., 2023) which has potential implications in terms of missed opportunities for EU's competitiveness (Hannan and Liu, 2023) and growth (Aghion et al., 2017; Gonzales, 2023). Within the EU territory, there is also a strong heterogeneity across Member States in terms of investment in AI (Evas et al., 2022; Maslej et al., 2023) and between EU regions regarding AI patent activities (Buarque et al., 2020; Cicerone et al., 2023). Therefore, understanding the drivers and conditions that enhances AI investment is also critical for addressing regional disparities.

Empirical literature on the determinants of the development of AI technologies is still at an early stage (Igna and Venturini, 2023). Some studies have emerged in the last years using AI patent data to assess the firm's probability to innovate in AI (Igna and Venturini, 2023) and how AI creation is correlated with regional technological knowledge production (Buarque et al., 2020). However, patent applications only capture part of the private and public investment activities in AI. Evas et al. (2022) conducted a first analysis in that direction by providing an estimate of the overall AI investments at EU Member States level. Two areas that have yet to be investigated in relation to the AI landscape are the regional dimension of the investment trends in AI[5] and the contribution of EU funds to these. Understanding the distribution of AI investment at regional level and the contribution of EU funding to it is crucial to deliver an even uptake of AI technologies at territorial level. It is important to ensure that AI uptake does not worsen the existing regional digital divide, and more broadly the economic one in Europe. To the best of our knowledge, there is no research covering both these topics.

The present paper aims to cover this gap by assessing the geographical distribution at NUTS 2-level of EU-funded investment (i.e. projects) related to AI during the programming period 2014-2020. Furthermore, it also examines the relationship between EU investment specialization in AI and territorial characteristics, as well as the links between smart specialization strategies and EU support to AI. For this analysis, we combine data from several sources, namely micro-datasets comprising the beneficiaries of 2014-2020 EU cohesion policy and Horizon 2020 funds, regional socio-economic indicators from Eurostat and information on investment priorities of the regional Smart Specialization Strategies (S3) from the European Commission's Eye@RIS3. To identify AI-related projects, we used text-mining

[5] Existing analysis on the geography of AI only use patent data (see e.g. Buarque et al., 2020; Cicerone et al., 2023).

techniques; then to assess the relationship between the degree of regional specialization on AI funded projects and several territorial characteristics, we use a spatial autoregressive model.

The interest for this research is two-fold. First, AI is considered a critical technology for Europe's economic security and future growth (European Commission, 2021a; 2023). However, investment in this field may depend on localization factors and constraints, as it is generally the case for emerging industries (Martin and Sunley, 2006), resulting in uneven concentration. Understanding these factors is important for the design of future policies aimed at creating a favorable environment for a wide-spread uptake of AI-related economic activities across Europe's territories. Second, the effects of AI have been wisely studied from the perspective of social inequalities, particularly in relation to its potentially disruptive impact on the labour market (Acemoglou and Restrepo, 2020; Aghion et al., 2019; Duch-Brown et al. 2022). However, an equally important complementary dimension that merits to be investigated is how AI technologies can affect territorial inequalities and what impact they can have on those, in particular if an uneven distribution of AI investments can exacerbate the territorial divide. Looking into the territorial determinants of AI EU-funded investments is a first step to grasp this dimension.

The present paper is divided in five sections. Section 2 provides a description of the definition of AI within the European context, as well, the research hypothesis. Section 3 describes the data and methodological approach. Section 4 presents the results of the analysis. Section 5 concludes and presents policy implications of this research.

2. Context and literature review

2.1 Definition of Artificial Intelligence and AI policy context in the EU

The term Artificial Intelligence (AI) has been used historically to identify a broad set of technologies that range from Natural Language Processing or Machine Learning to Deep Learning. References to Artificial Intelligence appeared already in the decade of the 50s of the 20th century (Nilsson, 2010) and since then, there have been multiple proposals to define it

According to (Samioli et al. 2021) there are more than 60 different definitions of AI technologies proposed by different research centers, standards developing organizations and public institutions. The large number of definitions shows the difficulty of defining Artificial Intelligence and indicates that most probably we will have to accept the co-existence of multiple of them that could be used depending on the pursued goal. Despite the multitude of existing AI definitions, there are nevertheless some common elements in most of them, as explained by Samioli et al. (2021). Some of the common features relate to the capacity of AI systems to perceive and interpret their surrounding environment; to collect, process and interpret inputs (typically in a massive way); to make decisions (including the ability of reasoning and learning); and to attain a set of specified goals in an autonomous way.

From the broad set of AI definitions, and due to its political relevance as the world's first attempt to regulate AI, our paper will stick to the definition proposed by the EU AI Act (European Commission, 2021a). This landmark piece of legislation defines Artificial Intelligence as "*software that […] can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with*".

As it can be seen the definition covers a wide range of capabilities, from problem solving and learning to natural language processing and perception. The definition of AI extends beyond mere automation, delving into the land of systems exhibiting cognitive functions that mimic, and sometimes surpass human intelligence for certain tasks, in line with the general features appearing in most of the AI definitions.

In an era of unprecedented technological advancement, AI stands as a transformative force, reshaping industries, economies, and societies worldwide, and it does so for three main reasons:

- Its pervasiveness, as most of the AI technologies could be characterized as general purpose technologies (Agrawal et al., 2019) and therefore virtually applicable to every economic sector;
- Its quick pace of adoption, as the uptake of AI technologies is occurring at a dramatically high speed (for instance, ChatGPT, a generative AI-based system, reached more than 100 million users in only two months);
- Its transformative capacity, as the capacity of AI systems to process huge volumes of data and their predictive (and even generative) capacity can impact dramatically the way organizations perform tasks (Acemoglou et al., 2019; Pratt, 2015).

Due to the already explained potential of AI to dramatically affect our economies and societies, the European Commission launched a series of initiatives with the main goal of ensuring that the EU is able to grasp all its benefits, making Europe a continent where AI can thrive, but also that societal and ethical risks of AI are managed and citizens' rights are fully respected. The main EU initiatives related to AI are listed below:

- The 2018 European Commission communication "*Artificial Intelligence for Europe*" (European Commission, 2018) with the goal of ensuring Europe remains competitive in the field.
- The "*EU Coordinated plan on Artificial Intelligence*" (European Commission, 2021b), adopted in 2019 and revised in 2021, including areas of strategic coordinated intervention by EU Member States and the European Commission to ensure European leadership in such key areas
- The "*proposal for a regulation laying down harmonised rules on Artificial Intelligence (AI Act)*" (European Commission, 2021a), the world's first ever regulation on AI, that has been recently adopted and will ensure a risk-based approach to the use of AI ensuring respect of citizens' right and privacy with the innovation capacity brought by the use of AI.

Additionally to the EU policy framework related to Artificial Intelligence, it is important to highlight the ambition of Europe to become the world's most digitalized continent by 2030, as expressed in the European Commission communication "2030 Digital Compass: the European way for the Digital Decade" (European Commission, 2021c). To do so, a number of indicators with regards digital infrastructures, connectivity, digital skills and use of emerging digital technologies, and in particular AI, are set and monitor by European authorities. The achievement of such goals throughout the different Member States of the EU is very much related to an even spatial distribution of the digital transformation and in particular of the uptake of AI.

2.2 Literature review and research hypotheses

To explore the regional dynamics of public support for AI in Europe, it is first important to delve into existing literature and identify the potential factors driving such support. Empirical evidence on the economic impact of AI has been limited for a number of reasons, most notably the lack of data at both firm and macro level and the difficulties in measuring progress in this technological area. Nevertheless, existing research so far suggests an overall positive impact on economic growth (see e.g. PwC 2018; Gonzales, 2023; He, 2019; Fan and Liu, 2021). However, Aghion et al. (2017), in a widely referenced article, note that the role of institutions and policies is crucial to steer positive outcomes and avoid adverse ones. This warning also applies to the effects of AI on the labour market, an issue that is receiving increasing academic attention. The widespread adoption of new technologies typically creates winners and losers by reshaping the demand for labour, with the risk of fuelling what Keynes called "technological unemployment" (Keynes, 1931). This is particularly true for a technology seen as very disruptive, such as AI (Brynjolfsson and McAfee 2014).

Some empirical studies have already identified a (predicted) risk of jobs losses or displacement due to the increasing use of AI, affecting not only middle-skilled workers (e.g. Acemoglu and Restrepo, 2019; Arntz et al., 2017), but also, to some extent, high-skilled ones (Webb, 2020). At the same time, the demand for AI-intensive jobs is growing rapidly in knowledge-intensive sectors such as ICT and financial services (Squicciarini and Nachtigall, 2021). Both these sectors are leading in terms of AI adoption and investment (McKinsey, 2017). Not surprisingly, empirical analysis show that the ICT sector as a whole has by far the highest share of AI-related patents (Dernis et al., 2019). A recent analysis by Igna and Venturini (2023) on the nature of European firms innovating in AI shows that they are more likely to be already active in ICT, particularly in the area of networking & communications, high-speed computing and data analysis, and more recently in cognition and imaging. It should be noted that the applications of AI concern an ever-greater number of sectors, as explained above, and its potential to become a ubiquitous technology, is evident. It is therefore not surprising that research on AI encompasses a wide range of scientific fields, such as mathematics, medicine, engineering, alongside computer science (Baruffaldi et al., 2020) or even philosophy or ethics. Finally, emerging digital technologies, such as AI, are further fuelling the clustering of innovation activities and industries (Brun et al., 2019; Rodriguez-Pose, 2020). Such agglomeration effects have been extensively discussed in the literature showing that most well-off and densely populated areas provide various location advantages to firms (Ottaviano and Puga, 1998; Glaeser, 2011).

Based on the above, it is clear that the development and implementation of AI is associated with a concentration of ICT activities, as a proxy for (i) large offer of skilled professionals in fields like computer science, data science, mathematics, and engineering; (ii) infrastructure and technology ecosystems like advanced computing infrastructure and cloud services; (iii) entrepreneurial culture on emerging digital technologies; (iv) access to high-quality data for training AI algorithms. It therefore seems important to consider ICT specialisation or concentration in a given territory as a potential determinant of public investment in AI.

Hypothesis 1: *A higher concentration of ICT activities tend to drive a higher specialisation of public investment in AI-related activities*

Recent studies (see e.g. Dernis et al., 2019; Igna and Venturini, 2023) have concluded that AI patenting is overall higher in companies that invest more in R&D or are more productive in terms of knowledge creation. At the same time, patent-holding firms generally appear to be more inclined to adopt AI (Bickley et al., 2023). This may indicate that more competitive regions with a higher innovation performance also attract more public funding for AI-related activities. Such a hypothesis can be seen from the broader perspective of the body of research that examines the spatial dynamics of public funding for innovation and industrial activities in Europe. Given the scope of the paper and its main objective to help fill the research gap on the regional dimension of AI-related public investment, it is important to briefly review relevant works in this area. More specifically, analyses of the territorial concentration of EU R&I funding (Horizon 2020) and cohesion policy funds offer a number of useful insights. First, regions with higher technological capacity and innovation performances tend to attract proportionally larger share of EU funds in competitive programmes such as Horizon 2020 (Archibugi et al., 2023; Molica and Santos, forthcoming). Second, a higher concentration of Horizon 2020 funding can be more generally observed in regions with higher GDP per capita (Dotti and Spithoven, 2018). This reflects the uneven spatial distribution of R&D, with a higher concentration in the most competitive regions (Fagerberg et al. 1997; Teirlinck and Spithoven 2005). Third, a more granular analysis, allowing to delve into the sub-regional dimension of funding distribution, which is particularly important for funds allocated to NUTS2-level regions such as for cohesion policy, shows the clustering of EU-funded innovation and industrial projects around cities as a result of agglomeration economies (Mieszkowskia and Barbero, 2021; Santos and Conte, 2024). The findings of the abovementioned studies can lead us to formulate a second hypothesis as to the spatial concentration of AI public investment.

Hypothesis 2: *More developed regions (more productive and/or more innovative) tend to be more specialised in public investment in AI*

Another aspect concerns market competition in a given territorial area. Aghion et al. (2005) demonstrated that the relationship between innovation and competition is not linear, assuming an inverted U-shaped relationship. Aghion (2017) defended that firms closer to the technological frontier tend to innovate more to stay ahead from the competition, while those lagging behind and striving to catch up may find the intensified competition daunting, leading them to innovate less. Therefore, a more competitive and dynamic market should, in principle, lead to more investment in AI. Since this seminal work of Aghion et al. (2005) many other authors found the same non-linear relationship, such as Crowley and Jordan (2017) and Friesenbichler and Peneder (2016) for Central and Eastern Europe and Central Asia, and Santos et al. (2018) for Portugal.

Hypothesis 3: *Investment specialisation in AI and competition display an inverted U-shaped relationship*

It is also important to consider the issue of public support for AI from a public policy standpoint: that is, as a result of specific economic objectives and sectoral and technological preferences formulated in the frame of regional or national innovation policies (Borrás and Edquist, 2013). This dimension is, in particular, key for the EU, as expressed in the European Commission communication "Artificial Intelligence for Europe" (European Commission, 2018), where the EU sets to itself the target to invest EUR 20 billion per year. One way to capture this dimension is to look at Smart Specialization Strategies or S3s (Foray at al., 2011). By adopting these strategies, which are a pre-condition to access EU cohesion policy funds, regional or national authorities identify areas or activities where they should focus their R&I efforts and investments to strengthen or diversify their productivity structure (Foray and Goenaga, 2013). There is an extensive body of research on the theoretical underpinnings and implementation of S3s, including from a critical perspective (e.g. Capello and Kroll, 2016; Radosevic, 2017; Hassink and Gong, 2019). On the other hand, only a handful of works have empirically explored the extent to which Smart Specialization Strategies are translated into coherent funding decisions, especially in the context of cohesion policy (D'Adda et al., 2019; Gianelle et al., 2019).

Hypothesis 4: *Investment specialization in AI is higher in regions who have identified it as a priority area in their Smart Specialization Strategies*

3. Data and methodology

Following the literature on geography of innovation (Balland, 2016; Cicerone et al., 2023), we measure the degree of regional specialization (DRS_i) by the ratio between the share of EU-funded projects related to AI in region i (S_i) expressed at NUTS 2-level and the share of EU-funded projects related to AI in the EU (S), as expressed in equation (1). A value of DRS_i higher than one indicates that region i is specialized in AI, since it concentrates a higher share of EU-funded projects related to AI than the EU average.

$$DRS_i = \frac{S_i}{S_{EU}} = \frac{\frac{AI_i}{TT_i}}{\frac{AI_{EU}}{TT_{EU}}} \tag{1}$$

In equation (1), AI refers to the total amount (EUR) of EU funds in region i (or at EU level) targeted to support AI investments. TT corresponds to the total amount (EUR) of EU-funds in region i (or at EU level). Under the present study, EU-funds come from the EU's research and innovation funding programme, Horizon 2020 (H2020) and 2014-2020 cohesion policy. As AI investment is often associated with the concept of innovation (e.g. development of new technology or the adoption of new process), we decided to focus on these two EU funding streams as they are the main ones aimed at enhancing Research and Innovation (R&I). In the case of cohesion policy, support for AI investments goes beyond the R&I area. This programme also supports projects related to the implementation of AI, namely in areas such as education and training (Table A1 in Appendix). Therefore, in order to have a complete picture of AI projects financed by cohesion policy, we decided to include in the present analysis all the typologies of AI funded investments.

Even though the two funding instruments mentioned above have different objectives, funding mechanisms, focus and management arrangements, they can complement each other and contribute to bridge the gap in access to finance in certain regions due to their different selection and allocation criteria. For this reason, in the context of this study, we decided to analyze both, rather than only one of them. For instance, H2020 is managed directly by the European Commission, with a strong focus on scientific excellence and collaboration, which is open to participants from all EU Member States and associated countries. On the other hand, cohesion policy funding programmes are implemented through partnership agreements between the European Commission and national authorities, its funds are managed by national or regional authorities and are allocated to EU regions based on their socio-economic development needs with the objective to achieve territorial convergence and competitiveness. For more details on the geographical distribution of funding under both programs, see section 4.

The list of beneficiaries of cohesion policy funds is extracted from the Kohesio platform and the list of projects funded by H2020 from the Horizon dashboard. AI-related investments are identified using text-mining techniques to projects' title and description. The list of keywords are extracted from the European Commission's report on the definition of AI (Samioli et al., 2020).

Given the use of data at NUTS2-level, with spatial units based on administrative boundaries it might be expected that a spatial dependence would exist. Therefore, to explain the degree of regional specialization in AI (DRS_i), the use of a spatial econometric model is recommended to avoid biased and inconsistent estimates by ignoring spatial effects (Anselin, 1988; LeSage and Pace, 2010). However, as the spatial econometric models include several specifications models – such as spatial autoregressive model (SAR), spatial error model (SEM) and spatial Durbin model (SDM), among others – to determine the most appropriate approach requires experimentation and estimating several tests (Florax et al., 2003; Baum and Hurn, 2021). For instance, equation (2) expresses a SDM where the dependent variable is explained by a set of territorial variables characterizing region i (X_i), the degree of specialization in neighboring regions j (DRS_j), and territorial characteristics in the neighbor regions j (X_j). The ρ, β and θ are the parameters to be estimated. The constant is expressed by α and the error term by u_i. W is a binary adjacency spatial weights matrix, assuming a value of 1 if region i and regions j are sharing a border and a value of 0 otherwise. The SDM assumes that the error term (u_i) is not explained by the error term in neighboring regions j (u_j) and spatial error coefficient (γ) is = 0. The SEM is obtained from equation (2) under the following conditions: ρ = 0, θ = 0 and $\gamma \neq 0$. The equation (2) corresponds to a SAR if $\rho \neq 0$, θ = 0 and γ = 0. The section 4.1 reports the results of the testing of the different conditions and the estimation strategy.

$$DRS_i = \alpha + \rho W DRS_j + \beta X_i + \theta W X_j + u_i \tag{2}$$
$$\text{where } u_i = \gamma W u_j + \varepsilon_i$$

The territorial characteristics included in the vector X_i are identified from the literature on drivers of AI investment as described in section 2 and include:

- The **regional concentration of employment in ICT services** as a proxy for the availability of ICT infrastructures and qualified human resources with digital skills. ICT services includes the economic activities: (i) telecommunications (NACE code 61), (ii) computer programming, consultancy and related activities (NACE code 62) and (iii) data processing, hosting and related activities; web portals (NACE code 63.1). The data are extracted from the Eurostat database on employment by economic activity [sbs_r_nuts06_r2 and; nama_10r_3empers], complemented by ORBIS BvD information when the information is missing. This concentration index is estimated following the approach described in equation (1) and it corresponds to the ratio of the share of employment in ICT services in region i over the share of employment in ICT services in the EU.
- **Territorial market competition** proxied by the inverse of the Herfindahl (1950) and Hirschman (1945) Index (HHI) using the sectorial concentration of employment of 56 economic

activities. As for the regional concentration ICT services index, data are extracted from the Eurostat database on employment by economic activity [sbs_r_nuts06_r2 and; nama_10r_3empers], complemented by ORBIS BvD information when the information is missing. Competition is estimated as expressed in equation (4), where $s_{i,j}$ corresponds to the share of employment in the economic activity n in region i, with n = 1, …, 56.

$$COMPETITION_i = \left(1 - \sum_{n=1}^{56} (s_{i,n})^2\right) \times 100\,, where \sum_{n=1}^{56} s_{i,n} = 1 \qquad (3)$$

- The **degree of innovativeness** of the region measured by the stock of patent application estimated using the perpetual inventory method and a depreciation rate of 5% following Cicerone et al. (2023). This variable estimated using OECD REGPAT and Eurostat data on population [nama_10r_3popgdp]. The stock is calculated using information starting in 1969.
- The level of regional development, measured by the Gross Value Added (GVA) per capita, following Cicerone et al. (2023), expressed in Purchasing Power Parity (PPP) and thousand EUR. This variable is estimated using Eurostat data [nama_10r_3gva, nama_10r_3popgdp].
- The commitment or preference in the context of regional innovation policies to target public investment to AI-related activities, captured by a dummy variable equal 1 if the AI-related investment is considered an innovation priority in the **Smart Specialisation Strategy** (or also called the Regional Innovation Strategy or S3) of the region. The list of innovation priorities for the EU territories in the programming period 2014-2020 is coming the Eye@RIS3 tool. The same methodological approach and list of keywords used to identify AI-related projects supported by EU funds is here utilized to identify territories with AI as an innovation priority in their 2014-2020 Smart Specialization Strategy. We apply text-mining techniques to S3 descriptions, using the list of keywords extracted from the European Commission's report on the definition of AI (Samioli et al., 2020). In the case of a national S3 (e.g. Portugal and Greece) or an S3 with a geographical coverage at NUTS 1 level (e.g. Belgium and Germany) with AI as an innovation priority, all NUTS 2 regions within it are classified as regions with AI as an innovation priority.

The spatial econometric model takes a cross-sectional form, where the dependent variable refers to the value of specialization in AI-related EU-funded projects in the programming period 2014-2020, executed until 2023. All the explanatory variables (except for the dummy variable S3) refers to the value in 2014 so as to capture the situation of the region at the beginning of the programming period 2014-2020 and to avoid reverse causality. The descriptive statistics of the variables are included in Table A2 in Appendix.

4. The geography of artificial intelligence-related EU-funded projects

Table 1 shows that around 8 EUR billion of EU funds coming from Horizon 2020 and cohesion policy were targeted to support AI-related investment in the programming period 2014-2020. We estimated that this amount represents an annual average of 7% of total investment in AI in the EU.[6] The share of EU funds relative to the total investment in AI tends to be higher in Central and Eastern European countries and – to a lesser extent – in Southern Europe. The main reason is that these countries benefit from significantly higher amounts of cohesion policy funds (Marques Santos et al., 2023) whilst generating less overall investment in AI. On the other hand, countries such as Belgium, the Netherlands or Finland, with a share of around 8%, are testament to the importance of Horizon 2020 funds in supporting AI-related activities in more well-off countries. It is noteworthy that, among the largest beneficiaries of EU funds, Spain and Poland appear to allocate or attract more EU resources to AI than Italy, Germany or France.

Table 1. Estimated average contribution of EU funds to support AI-related projects to total AI investment, programing period 2014-2020, by EU member states

Country	EU funds to support AI-related projects, Million EUR		AI investment, Million EUR (2020)	Average contribution of EU funds
	Total	Annual average		
	[1]	[2] = [1] : 7 years	[3]	[4] = [2] / [3]
Austria	197	28	480	5.9%
Belgium	274	39	449	8.7%
Bulgaria	52	7	26	28.5%
Croatia	65	9	72	12.9%
Cyprus	66	9	19	49.6%
Czech republic	170	24	240	10.1%
Denmark	134	19	389	4.9%
Estonia	28	4	45	9.0%
Finland	200	29	363	7.9%
France	687	98	3,301	3.0%
Germany	971	139	3,112	4.5%
Greece	276	39	97	40.6%
Hungary	169	24	84	28.8%
Ireland	138	20	2,092	0.9%
Italy	590	84	1,213	6.9%

Continues on the next page…

[6] Assuming an annual investment in AI constant over the period under analysis.

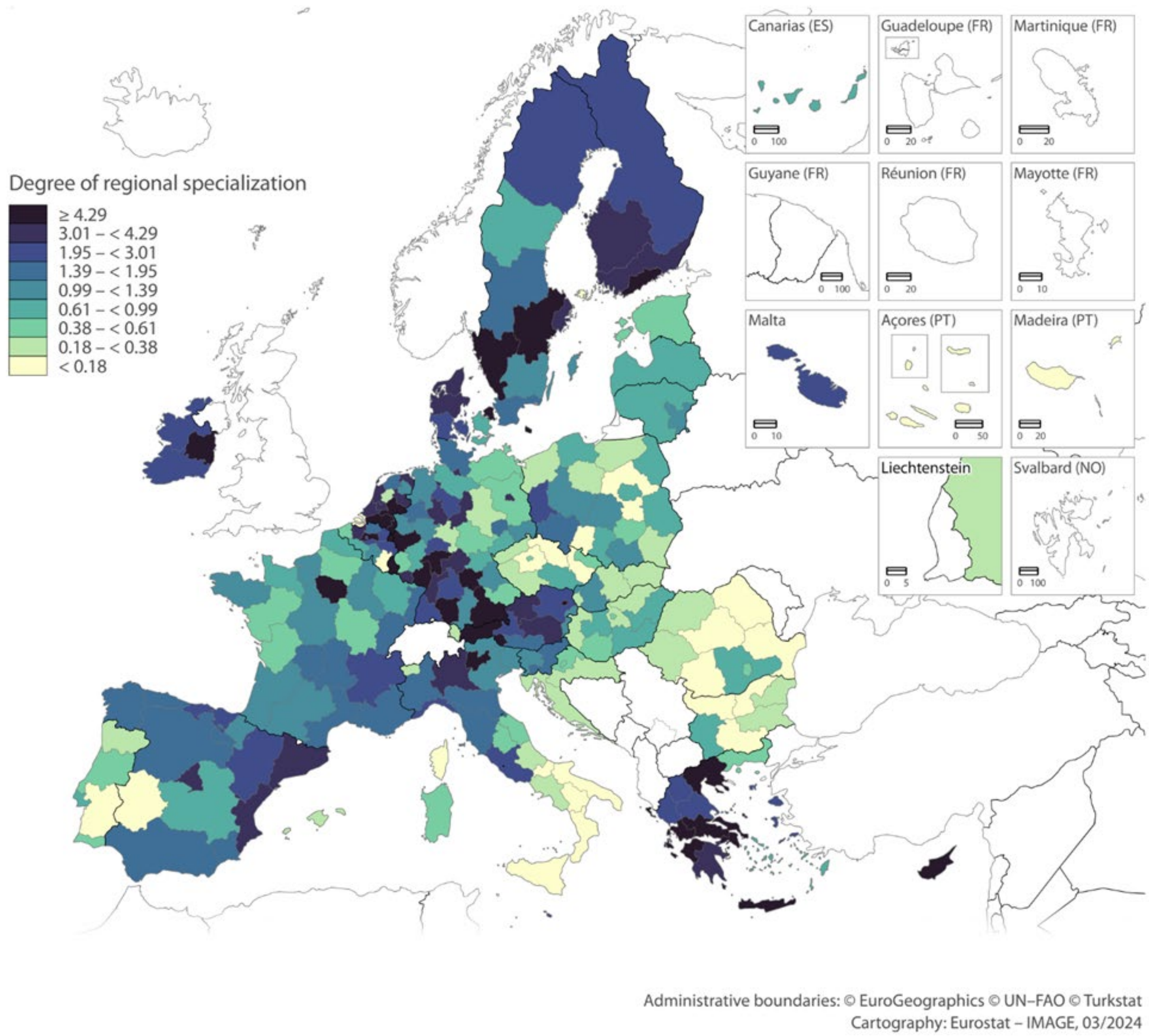
Table 1. Estimated average contribution of EU funds to support AI-related projects to total AI investment, programing period 2014-2020, by EU member states (continuation)

Country	EU funds to support AI-related projects, Million EUR		AI investment, Million EUR (2020)	Average contribution of EU funds
	Total	Annual average		
	[1]	[2] = [1] : 7 years	[3]	[4] = [2] / [3]
Latvia	45	6	30	21.3%
Lithuania	100	14	44	32.4%
Luxembourg	33	5	16	29.6%
Malta	7	1	12	8.7%
Netherlands	491	70	854	8.2%
Poland	1,375	196	507	38.7%
Portugal	153	22	198	11.0%
Romania	181	26	255	10.1%
Slovakia	59	8	134	6.3%
Slovenia	108	15	29	53.2%
Spain	1,162	166	1,298	12.8%
Sweden	228	33	614	5.3%
EU27	7,959	1,137	15,973	7.1%

Source: [1] Own estimation (see section 2) and [3] AI Watch (Eva et al, 2022).
Note: AI-related projects identified by text mining of title and project description. Values refer to the cumulative amount of investments under Horizon 2020 and Cohesion Policy in the 2014-2020 programming period.

The degree of regional specialization in AI-funded investment, measured by the regional share of EU funds allocated to AI in a territory in relation to the EU total, highlights core-periphery patterns (Figure 1). A higher concentration of funds can be observed in the most productive, as well as metropolitan regions of North-West and Southern Europe (e.g. Île-de-France, Madrid, Helsinki-Uusimaa). Conversely, Central and Eastern European regions, as well as Portugal, Italy's Mezzogiorno and some French and Spanish regions with a lower income than the national average, tend to have a much lower share. An interesting pattern is the high concentration of AI funded projects in Northern Sweden (Upper Norrland) and Finland (Northern and Eastern Finland), confirming the increasing importance of emerging sectors in the economies of these regions. More surprising is that several Greek regions (Attica, Eastern Macedonia and Thrace, etc.) show high levels of concentration vis-à-vis the EU total.

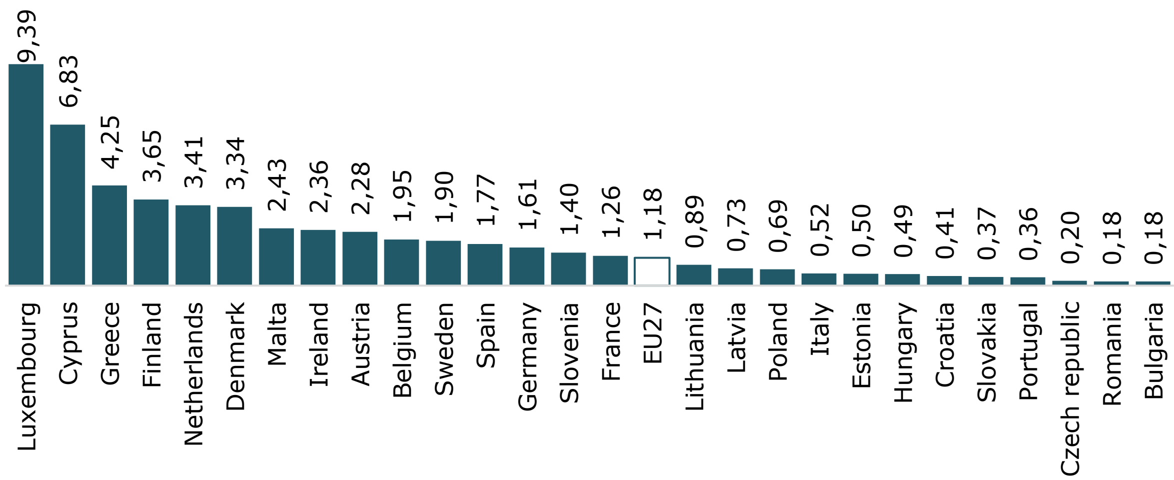
Figure 1. Degree of regional specialization on AI funded investment (benchmark: EU average), programming period 2014-2020, by Nuts 2 level



Source: Own estimation based on equation (1).

Note: AI-related projects identified by text mining of title and project description. Values refer to the cumulative amount of investments under Horizon 2020 and Cohesion Policy in the 2014-2020 programming period.

Figure 2. Degree of regional specialisation of EU-funded investments in AI by EU Member States (regional median)



Source: Own estimation based on data from Figure 1.

Note: Values refer to the country-median.

If we zoom in on the degree of regional specialisation in EU investment to AI by country (Figure 2), all Eastern countries together with Portugal and Italy report a value of this indicator below the EU median, while the North-West EU countries show values above the EU median. This suggests that the degree of specialisation is strongly correlated with the level of development.

Finally, the intensity of subsidized investment in AI, expressed in per capita terms (Table 2), illustrates well the different spatial distribution of the contribution of the two EU instruments to the financing of AI-related investments. The average per capita H2020 funding allocated to AI is significantly higher in more developed regions than in transition and less developed ones. On the other hand, less developed regions have an even higher average per capita amount of cohesion policy funding targeted to AI vis-à-vis the other two categories. This shows a strong complementarity of the two instruments, allowing less developed regions to benefit from AI-related funding even if their capacity to access H2020 funds is lower (Dotti and Spithoven, 2018).

Table 2. Subsidized investment in AI per capita, PPS, by funds and category of region

Region category	H2020		Cohesion policy		Both	
	Median	Mean	Median	Mean	Median	Mean
More developed	9.78	14.59	0.93	4.16	11.86	18.76
Transition	2.48	4.62	2.06	3.14	5.17	7.77
Less developed	1.29	3.56	9.78	23.13	15.59	26.68

Source: Own elaboration based on data from Horizon dashboard and Kohesio platform.

Note: Region category refers to the 2014-2020 cohesion policy classification.

5. Results

5.1 Spatial econometric model selection

Following Florax et al. (2003), to identify the spatial econometric model that best fits the data, we first estimated the Moran I (Moran, 1950) and Lagrange Multiplier (LM) tests (Table 3). The result of the Moran I test reveals that spatial dependence occurs and spatial models should be used. The results of the LM test for spatial error and spatial lag then indicate that the lag specification (SAR) should be used against the spatial error model (SEM).

Table 3. Diagnostic tests for spatial dependence in OLS regression

Test	Statistic	df	p-value
Spatial error:			
Moran's I	4.453	1	0.000
Lagrange multiplier	14.922	1	0.000
Robust Lagrange multiplier	0.000	1	0.982
Spatial lag:			
Lagrange multiplier	20.851	1	0.000
Robust Lagrange multiplier	5.929	1	0.015

Source: Own elaboration based on equation (2) without considering spatial effects (WY, WX and Wu).

To confirm our previous findings and to compare the performance of different spatial econometric models, we follow the procedure described by Baum and Hurn (2021), which consists in comparing the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the different model specifications. Table 4 reports the results of AIC and BIC for six different spatial econometric models. The best model is typically the one with the lowest value of AIC and BIC. Comparing the AIC and BIC of the SAR and SEM, we confirm the previous findings, that a SAR is preferred to a SEM. However, when comparing the SAR with the SDM, AIC and BIC lead to different conclusions. Raftery (1995) developed guidelines for interpreting changes in BIC between two models that differ in terms of the number of parameters. This author suggests to favor a model that leads to a decrease of the BIC value higher than 2. McCoach and Cintron (2022) propose an approach to apply to AIC. If the ratio between the difference in the AIC deviances of the two models divided by the number of difference in the number of estimated parameter is less than 2, they suggest favouring the more parsimonious (less parameterized) model. Indeed, as moving from a SAR to SDM increase model complexity by incorporating additional parameters, one should assess if complexity is not leading to overfitting. Models that achieve good fit while using fewer parameters should be favored over more complex that achieve similar fit but with more parameters.

Table 4. Results model comparison test: Akaike's information criterion (AIC) and Bayesian information criterion (BIC)

Model	Spatial lag(s)	N	ll(null)	ll(model)	df	AIC	BIC
Non-Spatial (OLS)	-	235	-444.24	-396.51	7	807.03	831.24
SAR, Spatial autoregressive model	WY	235	.	-387.18	9	792.36	823.50
SEM, Spatial error model	Wu	235	.	-388.59	9	795.18	826.32
SLX, Spatial lag of X model	WX	235	.	-386.86	14	801.71	850.15
SAC, Spatial autoregressive combined model	WY, Wu	235	.	-387.02	10	794.04	828.63
SDM, Spatial Durbin model	WY, WX	235	.	-380.40	15	790.80	842.69
SDEM, Spatial Durbin error model	WX, Wu	235	.	-381.08	15	792.17	844.06

Source: Own estimation based on equation (2) and imposing different restrictions.

Note: Complete specifications of the different models available upon request.

Using the criteria of Raftery (1995), we observe that when adding more parameters (e.g. with SLX, SAC, SDM and SDEM) generates a change in BIC, compared to that of the SAR[7], higher than 2. Following McCoach and Cintron (2022), and comparing the AIC of the SAR with the two lowest AICs (SDM and SDEM) we observe that the ratio between the change in the AIC over the change in the number of parameters[8] is lower than 2. Thus, using both arguments there is evidence in favor of the SAR over the other models. Therefore, we focus our interpretation on the SAR in the next section.

We also checked for the presence of outliers in our dependent variable (i.e. observations that deviate significantly from the rest of the data) using a box plot (see Figure A1 - left in the Appendix). Some extreme values seem to be observed at the 95th percentile and to normalise the data we use the Winsorisation technique. In this approach, all values above the 95th percentile are replaced by the value at the 95th percentile. After winsorisation, we checked for changes in the summary statistics, the distribution of the data (see Figure A1 - right in the appendix) and the relationship between variables (Table A4 in the Appendix). Winsorisation helps to improve the quality of the model specification by looking at the change in Pseudo R2 (0.3197 versus 0.3502) and Log Pseudolikelihood (-424.10 versus -387.18) without unduly distorting the overall data structure.

5.2 Drivers of EU-funded investment related to AI

Table 5 reports the results of the SAR (equation 2) estimated using maximum likelihood in column (2) and generalized spatial two-stage least squares in column (3). Column (1) reports the results of a Pooled OLS without spatial effects for comparison purpose. The results of the Wald test of spatial terms displayed at the bottom of Table 5 reveal the evidence of spatial dependence in the model, as already noticed in the results of Table 3. This implies that the value of regional specialization in AI in region i is

[7] Change in BIC: SAC versus SAR = 5.13 ; SDM versus SAR = 19.19 ; SLX versus SAR = 26.64 ; SDEM versus SAR = 20.56.

[8] Change in AIC over change in the number of parameters: SAR versus SDM = 0.261; SAR versus SDEM = 0.033.

influenced by the values of the same variable in neighboring regions, and ignoring it can lead to biased parameter estimates, as reported in column (1) compared with column (2) and (3). The results of the Ramsey Regression Equation Specification Error Test (RESET) to detect specification errors in the model demonstrates that the model has no omitted variables. To confirm that the estimates are also not biased by the presence of multi-collinearity between the different explanatory variables, Table A3 in Appendix reports the results of the correlation matrix and variance inflation factor (VIF). A sensitivity analysis is also available in Table B1 and Table B2 in Appendix, showing that our results are robust in relation to different combination of explanatory variables.

Table 5. Results of spatial autoregressive (SAR) model, dependent variable: degree of regional specialization in AI (DRS_i)

Variables	**Pooled OLS**	**SAR**	
		Maximum likelihood	**Generalized spatial two-stage least squares**
	(1)	(2)	(3)
Regional specialisation in ICT services	0.277	0.461**	0.482**
	(0.216)	(0.193)	(0.215)
Competition	6.624***	6.290***	6.253***
	(1.419)	(1.868)	(1.399)
Competition – Squared	-0.0380***	-0.0359***	-0.0357***
	(0.00807)	(0.0106)	(0.00795)
Smart Specialisation (Yes/No)	0.344*	0.344**	0.344**
	(0.180)	(0.169)	(0.169)
Stock of patents	0.0418***	0.0371***	0.0365***
	(0.0152)	(0.0113)	(0.0117)
GVA per capita	0.0581***	0.0336**	0.0309*
	(0.0128)	(0.0133)	(0.0168)
W.Y	-	0.304***	0.338**
	-	(0.0702)	(0.133)
var(u.Y)	-	1.545***	-
	-	(0.185)	-
Constant	-288.8***	-275.4***	-273.9***
	(62.26)	(82.14)	(61.45)
Observations	235	235	235
R-squared / Pseudo R-squared	0.3338	0.3502	0.3501
Log pseudolikelihood	-	-387.18	-
Joint significance (p-value)	0.0000	0.0000	0.0000
Wald test of spatial terms (p-value)	-	0.0000	0.0113
Ramsey test for omitted variables (p-value)	0.0585	0.2327	0.2212

Note: Robust standard errors in parentheses.

Significance level: *** p<0.01, ** p<0.05, * p<0.1.

The spatially lagged dependent variable (W.Y) shows a positive and significant coefficient, based on the results in column (2) and (3), meaning that an increase in regional specialization of investment in AI in neighboring regions is associated with an increase in the regional specialization in AI in region i. This spatial dependence also indicates the presence of spatial spillovers effects and externalities coming from the interactions between the different EU regions. This is in line with previous studies providing evidence of the presence of spillovers from publicly funded projects (see e.g. Scotti et al., 2022; Becker et al. 2023). However, the present study goes beyond the positive externalities of EU funds, it reveals externalities in terms of the concentration and specialization of EU funds in a specific area, namely in AI. This suggests that specialization in region i is interrelated with the same specialization in adjacent regions, probably due to the benefit of geographical proximity, enabling easier knowledge transfer (Torre, 2008) and the possibility of sharing of resources (human and capital) within a single market economy, like the one of the EU.

The degree of regional specialization of EU-funded investment in AI is also positively correlated with the region specialization in ICT services, as well as the degree of innovativeness (proxied by patent stock) and level of development (measured by the GVA per capita) of the region. This supports our hypotheses 1 and 2, respectively. These findings are also aligned with the cluster theory (Porter, 1998) and agglomeration economy theory (Krugman, 1991): industries tend to concentrate geographically in specific areas, characterized by a strong interconnectedness of the different players along the value chain, and such concentration generates economies of scales and agglomeration effects. In the framework of the present study, this reveals that pre-existing sectorial specialization in ICT services, as a proxy for the availability of ICT infrastructures and qualified human resources, fosters specialization of EU funds in AI-related activities. Indeed, regions with better pre-conditions in place to develop AI projects tend to attract more AI investments and/or to generate more AI knowledge internally. On the other side, as we consider AI as a disruptive innovation, it is also expected that, under the so-called Myrdal (1957) effect and the principles of cumulative knowledge and positive feedback loop, additional innovation tend to be concentrated across territories which are already more innovative and competitive (Fagerberg et al., 1997; Teirlinck and Spithoven, 2005).The level of sectorial competition in the region displays a statistically significant inverted-U relationship, in line with Aghion et al. (2005) and our hypothesis 3. This indicates that regions with a higher level of competition tend to exhibit a higher specialization of funds in AI, although when faced with higher competition pressure this specialization patterns tend to decrease. Under the assumption that AI is considered as a disruptive innovation, market competition creates incentives for firms to specialize more in AI (instead of other activities) to outperform their competitors. However, under excessive competition, firms are discouraged to commit more efforts on AI-related activities, potentially due to higher risk-taking for profit maximization.

Lastly, the results of our estimates in Table 5 also displays that having AI as a priority in the innovation policy of a region is positively associated with a higher specialization on EU-funded projects related to AI, supporting our hypothesis 4. This finding is particularly interesting because it shows the alignment between political commitments to prioritize AI-related activities in regional innovation policies (as described in the Smart Specialization Strategies of the territories) and the use of EU funds for this purpose. It may also reveal coherence between innovation strategies and the selection of projects to be implemented in regions (D'Adda et al., 2019; Gianelle et al., 2019), as well as policy effectiveness. Indeed, if there is a close match between the main stated priorities of public investment and the actual/real allocation of funds, it suggests that policy goals are being translated into concrete actions.

6. Conclusion and policy implications

This paper assesses the geographical distribution at NUTS2-level of EU-funded investments related to AI. It uses information on projects implemented by the two major EU funding programmes: Horizon 2020 and cohesion policy during the programming period 2014-2020. Results show that during this period, around 8 billion EUR of EU funding has been targeted to AI investments in the European regions, which contributed to 7% of the total annual AI investments in recent years. However, some countries, such as Greece, Cyprus, Slovenia and Poland, turned out to be more dependent on EU funds to finance AI investments than others.

Using a spatial autoregressive model, this study also examines the relationship between specialization patterns of EU funds in relation to AI-related projects and regional characteristics. Considering AI as a disruptive innovation, our findings demonstrate that more innovative and developed regions tend to show a higher specialization of public investment in AI-related activities. Moreover, the specialization of a region in ICT services also seems to be an important driver explaining the specialization in funding AI-related projects. Overall, these conclusions are related to the concept of agglomeration economies and the Myrdal (1957) effect. Another important conclusion arising from the analysis is the positive relationship between the stated innovation priorities of a region and the specialization of EU funding. To the best of our knowledge, this has never been tested before, and could be synonymous with policy effectiveness in resource allocation. Regional competition displays an inverted U-shaped relationship with the degree of regional specialization, implying that competition pressure drives AI specialization, but only up to a certain threshold.

In terms of policy implications, this study has several important highlights. It shows that the current push to boost Europe’s industrial and research capacity in the field of AI needs to carefully consider the potentially significant regional implications, also to ensure the EU’s target of investing EUR 20 billion per year in AI by 2030. Using EU funding as proxy of public investment, our analysis sheds light on the fact that AI-related investment is already highly spatially concentrated, which might deepen existing territorial disparities given the growing economic relevance of the technology. Public policies at EU, national and regional level should address this risk by continuing to target the root causes of Europe’s innovation divide: education, demography and quality of institutions, among others.

Understanding the Myrdal (1957) effect has important implications for reducing spatial imbalances, as according to this theoretical framework, regions that initially lag behind in terms of AI development may find it difficult to catch up at a later stage with more advanced regions, as they lack the necessary resources and infrastructure to compete effectively. Our findings confirm the importance of investing in digital skills and ICT qualifications, as well as digital infrastructures, in line with the ambitions and targets of Europe’s Digital Decade (European Commission, 2021c), as a precondition for attracting significant funding (and investment) for AI-related projects.

Moreover, creating the conditions to foster competition is beneficial for fostering AI; however, it is important to strike a balance and avoid creating conditions for excessive competition that could disincentive additional investment in AI.

Additionally, our findings show complementarity between the AI-related investment funded by H2020 and cohesion policy. The possibility for less-developed regions to access pre-allocated cohesion funds and devote them to AI-related opportunities is combined and complemented with the possibility for more innovative regions to use H2020 funds to boost their AI ecosystems. This effect mitigates, at least partially, the divide between regions within EU, helping in a more even distribution of AI investments. It also underlines the importance of maintaining a cohesion policy with an adequate budget and a place-based focus in the future.

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Appendix

Appendix A. Descriptive statistics, multi-collinearity analysis and outliers' detection

Table A1. EU-funded investment in AI-related activities, cohesion policy 2014-2020, by thematic objective (% total AI under cohesion policy)

Thematic Objective (TO)	% EU funds
TO01 - Research, technological development and innovation	74.0%
TO02 - Information and communication technologies	9.41%
TO03 - Small and medium-sized enterprises	9.34%
TO10 - Education and training	3.02%
TO11 - Efficient public administration	1.29%
TO09 - Social inclusion	1.01%
TO08 – Employment	0.82%
TO06 - Protecting the environment	0.50%
TO04 - Low-carbon economy	0.34%
TO07 - Sustainable transport	0.24%
TO05 - Climate Change	0.01%

Source: own elaboration based on Kohesio data.

Table A2. Descriptive statistics: mean, standard deviation, minimum and maximum

Variable	Obs	Mean	Std. dev.	Min	Max
Regional specialization on AI investment	235	1.73	1.61	0.00	5.45
Regional specialization on ICT services	235	0.80	0.61	0.11	2.54
Competition (1-HHI)	235	88.81	2.54	81.84	93.16
Artificial intelligence as priority in S3 (Yes/No)	235	0.4	0.49	0	1
Stock of patents (1.000 number)	235	3.02	8.17	0.00	83.01
GVA per capita (1.000 EUR, PPS)	235	23.38	9.41	6.78	70.24

Source: Own elaboration.

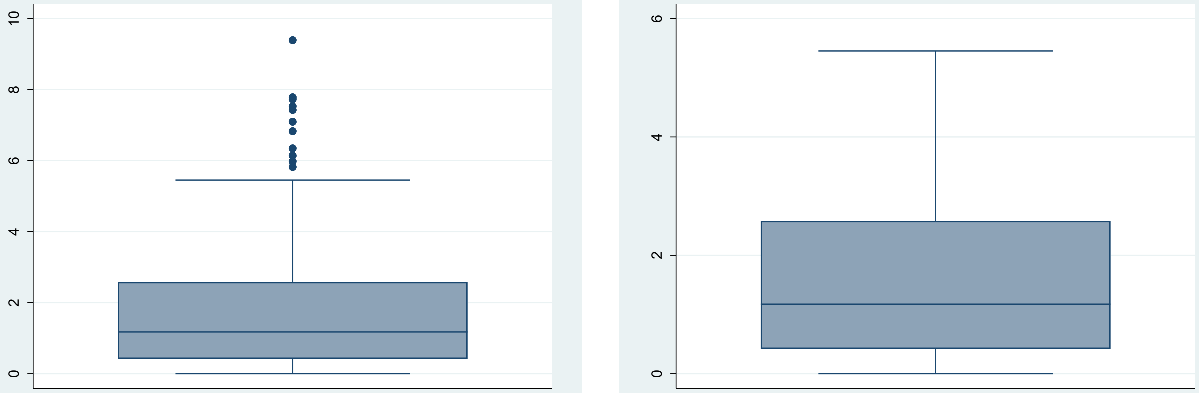
Table A3. Correlation matrix and variance inflation factor (VIF)

#	Variables	VIF	Correlation matrix				
			1	2	3	4	5
1	Regional specialization on ICT services	2.04	1				
2	Competition (1-HHI)	1.09	0.25	1			
3	Artificial intelligence as priority in S3 (Yes/No)	1.03	0.05	-0.06	1		
4	Stock of patents (1.000 number)	1.29	0.40	0.19	0.05	1	
5	GVA per capita (1.000 EUR, PPS)	2.12	0.70	0.24	-0.06	0.44	1
	Mean VIF	1.51					

Source: Own elaboration.

Figure A1. Box plots regional specialization before (left) and after (right) winsorization

Before winsorization	After winsorization



Before winsorization	After winsorization
Obs: 235	Obs: 235
Mean: 1.809	Mean: 1.732
Median: 1.175	Median: 1.175
P(95): 5.452	P(95): 5.452
Max: 9.392	Max: 5.452

Source: Own elaboration.

Table A4. Results of spatial autoregressive (SAR) model before and after winsorization, maximum likelihood estimates, dependent variable: degree of regional specialization in AI

Variables	Before winsorization (1)	After winsorization (2)
Regional specialisation on ICT services	0.488**	0.461**
	(0.227)	(0.193)
Competition	6.992***	6.290***
	(2.193)	(1.868)
Competition – Squared	-0.0399***	-0.0359***
	(0.0125)	(0.0106)
Smart Specialisation (Yes/No)	0.420**	0.344**
	(0.198)	(0.169)
Stock of patents	0.0313**	0.0371***
	(0.0133)	(0.0113)
GVA per capita	0.0465***	0.0336**
	(0.0156)	(0.0133)
W.Y	0.252***	0.304***
	(0.0739)	(0.0702)
var(u.Y)	2.131***	1.545***
	(0.321)	(0.185)
Constant	-306.4***	-275.4***
	(96.41)	(82.14)
Observations	235	235
Pseudo R-squared	0.3197	0.3502
Log pseudolikelihood	-424.10	-387.18
Joint significance (p-value)	0.0000	0.0000
Wald test of spatial terms	0.0000	0.0000

Source: Own elaboration.

Note: Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Appendix B. Sensitivity Analysis

Table B1. Pooled OLS, dependent variable: degree of regional specialization in AI ($\mathrm{DRS_i}$)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Regional specialisation on ICT services	1.076***	-	-	-	-	-
	(0.198)	-	-	-	-	-
Competition (1-HHI)	-	0.0318	6.966***	-	-	-
	-	(0.0349)	(1.792)	-	-	-
Competition (1-HHI) - squared	-	-	-0.0394***	-	-	-
	-	-	(0.0102)	-	-	-
Stock of patents (1.000 number)	-	-	-	0.0758***	-	-
	-	-	-	(0.0182)	-	-
Artificial intelligence as priority in S3 (Yes/No)	-	-	-	-	0.395*	-
	-	-	-	-	(0.218)	-
GVA per capita (1.000 EUR, PPS)	-	-	-	-	-	0.0831***
	-	-	-	-	-	(0.0111)
Constant	0.874***	-1.093	-306.0***	1.503***	1.574***	-0.210
	(0.158)	(3.087)	(78.42)	(0.105)	(0.127)	(0.255)
Observations	235	235	235	235	235	235
R-squared	0.168	0.003	0.039	0.149	0.015	0.237

Source: Own elaboration.

Note: Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table B2. Sensitivity analysis - Results of spatial autoregressive (SAR) model, Maximum likelihood estimates, dependent variable: degree of regional specialization in AI ($\mathrm{DRS_i}$)

Variables	(1)	(2)	(3)	(4)	(5)
Regional specialisation on ICT services	-	0.423**	0.511***	0.545***	0.769***
	-	(0.197)	(0.194)	(0.195)	(0.149)
Competition	6.140***	-	6.602***	5.835***	6.571***
	(1.894)	-	(1.878)	(1.901)	(1.879)
Competition – Squared	-0.0350***	-	-0.0377***	-0.0333***	-0.0374***
	(0.0108)	-	(0.0107)	(0.0108)	(0.0107)
Smart Specialisation (Yes/No)	0.395**	0.400**	-	0.389**	0.288*
	(0.170)	(0.172)	-	(0.172)	(0.168)
Stock of patents	0.0407***	0.0332***	0.0390***	-	0.0426***
	(0.0114)	(0.0115)	(0.0114)	-	(0.0111)
GVA per capita	0.0547***	0.0353***	0.0299**	0.0427***	-
	(0.0104)	(0.0135)	(0.0133)	(0.0131)	-
W.Y	0.268***	0.319***	0.302***	0.320***	0.366***
	(0.0695)	(0.0713)	(0.0711)	(0.0701)	(0.0674)
var(u.Y)	1.590***	1.621***	1.573***	1.611***	1.568***
	(0.184)	(0.199)	(0.194)	(0.189)	(0.186)
Constant	-269.2***	-0.205	-288.7***	-256.1***	-287.8***
	(83.26)	(0.257)	(82.57)	(83.59)	(82.63)
Observations	235	235	235	235	235
Pseudo R-squared	0.3381	0.3064	0.3352	0.3182	0.3088
Log pseudolikelihood	-389.95	-393.11	-389.24	-392.40	-390.18
Joint significance (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Wald test of spatial terms	0.0001	0.0000	0.0000	0.0000	0.0000

Source: Own elaboration.

Note: Robust standard errors in parentheses. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

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