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OK Computer: The Creation and Integration of AI in Europe

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OK COMPUTER: THE CREATION AND INTEGRATION OF AI IN EUROPE

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ABSTRACT

This paper investigates the creation and integration of Artificial Intelligence (AI) patents in Europe. We create a panel of AI patents over time, mapping them into regions at the NUTS2 level. We then proceed by examining how AI is integrated into the knowledge space of each region. In particular, we find that those regions where AI is most embedded into the innovation landscape are also those where the number of AI patents is largest. This suggests that to increase AI innovation it may be necessary to integrate it with industrial development, a feature central to many recent AI-promoting policies.

JEL: O33, O31, R11

Keywords: Artificial Intelligence; Geography of Innovation; Knowledge Space; Technological Change; Regional Studies

1 Introduction

Artificial Intelligence (AI) has become one of the most high-profile areas for technological development and potential regional economic growth opportunities. In the public arena, AI has captured a degree of attention that outstrips other less sensational but no less important fields of research (e.g. green technologies). In the academic literature, AI has already generated a body of research on its implications for labour markets (OECD, 2017), growth (Aghion et al., 2017), and international trade (Goldfarb and Trefler, 2018). A key aspect of this debate is that AI has the potential to automate routine, non-cognitive tasks that have been primarily performed by middle-skilled workers. Furman and Seamans sum up the idea nicely, commenting that the growth of AI "has led both to excitement about the capacity of technology to boost economic growth and to concern about the fate of human workers in a world in which computer algorithms can perform many of the functions that a human can" (Furman and Seamans, 2019, p. 161). Frey and Osborne (2017) measure the likelihood of occupations becoming automated with the growth of AI by breaking each occupation down into its component tasks, then assigning a probability of automation to each task. Acemoglu and Restrepo (2019) also take a similar task-based approach. The easier the component tasks are to automate, the more likely an occupation will see humans replaced by AI with some occupations under significant risk. AI has the potential for significant shifts in the employment and income distributions of regions (Agrawal et al., 2019; Arntz et al., 2016; Atack et al., 2019; Korinek and Stiglitz, 2017; OECD, 2017). Despite much speculation on the potential socio-economic impacts of this new stream of technology, there is no doubt that due to its productivity enhancing capabilities (Brynjolfsson et al.,

2018) developing a strong AI research base has become a primary goal for many leading economies. This has led to the implementation of various policies encouraging AI development. For example, Canada paved the way in 2017 by including a C$125 million budget for the development of its AI research capabilities. This was quickly followed by Germany, the US, the UK, China, and multilateral institutions including the European Union.[1]

Despite all of this interest, little is known about the development of AI technologies. Part of this gap is due to the challenge in defining the concept itself. AI can cover existing methodologies such as machine learning that some may argue are certainly artificial but are not "intelligent", developing applications such as autonomous automobiles, and the potentially impossible creation of a sentient machine. Further complicating the understanding of how AI innovation fits into the overall research and development picture is the fact that it is not the result of a single coherent technological base, but is rather a construct emanating from the recombination of many previously existing technological foundations. Taking advantage of the fact that patents are considered the best option for intellectual property protection in AI technology development, one way forward is to investigate the technological codes which underpin development of an invention (Office, 2018). Investigating these codes that are based on the Cooperative Patent Classification (CPC) scheme has proven useful in previous studies where the identification and subsequent diffusion of a novel product or process of economic value has been the object of inquiry (Feldman et al., 2015). Unfortunately, there is no single CPC technology class specific to AI.[2] To our knowledge, there is not yet a picture of how AI creation is distributed across European regions and how it interacts with the overall innovation structure within a given region. This is the gap the current paper fills by describing the amount and inter-connectedness of AI patents in 230 European NUTS2 regions from 1980 to 2013.[3] We do so by first using a keyword/CPC matching algorithm on the abstracts of over 1.4 million patent applications to identify those related to AI. We find approximately 5,300 AI patents, which tend to be clustered in twelve four-digit CPC codes out of the over 650 codes that make up the entire classification scheme. Although these twelve codes contain non-AI technologies as well, the bulk of AI patents fall into a small number of codes focused on computing (CPC code G06, with G06K, G06T, and G06F particularly common). Second, we then identify which regions have become "AI superstars", and produce the most AI patents. These superstars are especially important, as the top 10% of regions create 39.3% of all European AI patents.

Perhaps unsurprisingly, these regions also dominate our AI-containing CPC codes. This then suggests that the factors that support the development of computing-related technology may be necessary to spur the development of AI. Such a finding is indeed what one would expect based studies of the evolution of regional technological development (Kogler et al., 2013; Boschma et al., 2015). Guided by an Evolutionary Economic Geography (EEG) framework (Kogler, 2015), this literature highlights how regional technological change is shaped by path-dependent processes (Martin and Sunley, 2006). These processes hing on the composition of knowledge and technology. This sets the stage for regional diversification with the direction dependent on cognitive relatedness between existing and new technologies (Boschma, 2017; Kogler, 2017). Thus, the feasibility to enter a new area of technology, such as AI, is largely determined by the set of existing capabilities, such as computing, which are themselves largely historic and place-specific. While these theories have been tested at the aggregate level (Kogler et al., 2017) our analysis extends the approach to the technology-specific sectoral level.

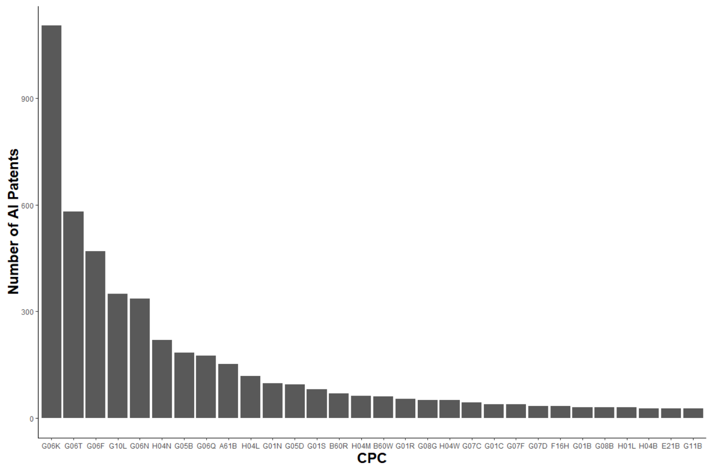
The next step of the analysis shifts the focus to a detailed investigation of how AI patents fit into a region's overall technological knowledge producing landscape. Utilizing the knowledge space methodology of Kogler et al. (2013, 2017), which takes advantage of the co-occurrence network of CPC codes found on individual patent documents, the objective is to construct a series of indicators that describe the inventive network of a region. We then estimate how these indicators change when omitting the AI patents, which gives us insight into how central those patents are to the region's knowledge space. When doing so, we find that those regions that have the most AI patents also tend to be those where AI is most connected to the overall knowledge space, i.e. in their absence there is a significant shift in the inventive network structure. This suggests that in order to emerge as an AI superstar it may be important to ensure that those patents are well-connected to other research and development activities. This in turn suggests that to establish a foothold in this area, developing AI hand-in-hand with applications (such as image recognition for use in autonomous automobiles) may be more fruitful than developing it as an isolated technology. This confirms insights from EEG driven empirical research highlighted above, and considering that this approach forms a central pillar of many of the government-led AI development policies discussed in (Dutton, 2018), suggests that government policy may be on the right track.

[1]For a good overview of the various policies that have been implemented, see (Dutton, 2018). Details on the EU's strategic AI policy can be found in (Commission, 2018). The effects of China's emphasis in robotics can be seen in (Cheng et al., 2019).

[2]Papers such as (Acemoglu and Restrepo, 2017) or (Graetz and Michaels, 2018) use data from the International Federation of Robotics to estimate sectoral and regional exposure to automation via the concentration of robots in those areas. However, the dataset adopted by the authors simply uses the presence of robots in an industry as a proxy for AI and growth, an imperfect measure that offers only limited inference.

[3]We end our analysis in 2013 due to the well-known issue of end of sample truncation in patent data.

Figure 1: Count of AI Patents by CPC Code



This paper proceeds as follows. Section 2 describes the identification of AI patents as well as the main CPC codes and regions in which they are found. Section 3 analyzes how those AI patents fit into the knowledge spaces of the main AI regions. Finally, Section 4 concludes.

2 Identifying AI Patents

The first step in the analysis is identifying AI patents. As previously discussed, there is no CPC code specifically for AI. We therefore apply a keyword identifier to the European Patent Office's (EPO) PATSTAT database which covers European patents from 1980-2013. PATSTAT provides the patent text itself along with patent and inventor metadata such as priority year, inventor address, and CPC codes. To identify AI patents, we take the abstract text of each patent and perform a keyword search to identify AI-related terms. We use this search to classify each patent in our dataset as "AI" or "Non-AI". Obviously, this approach relies on the choice of identifiers. For the results presented here, we use the combination of keywords and CPC codes (well beyond the 4-digit aggregate level) that are indicative of AI as proposed by the World Intellectual Property Organization (WIPO) (WIPO, 2019) as we believe it gives a more recent and specific definition of AI. In robustness checks, we use the identifying keywords developed by (Cockburn et al., 2018) and reach comparable conclusions.[4]

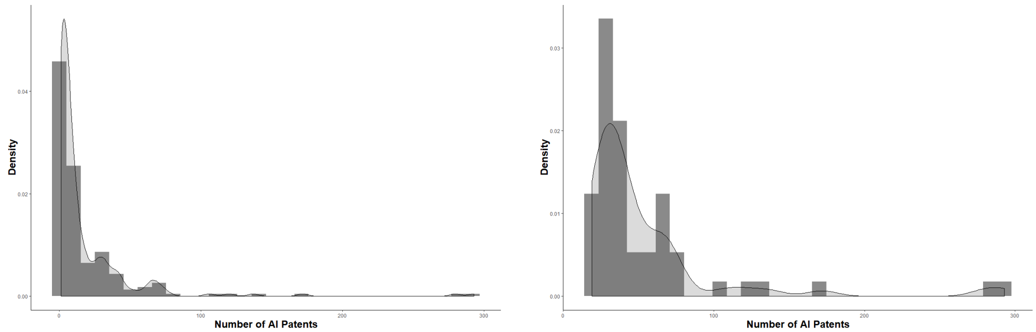
This process identifies 5,312 AI patents out of the 1.4 million in PATSTAT. Thus, although everyone certainly seems to be discussing AI, very few have been able to successfully patent the technology so far. The first issue to explore is in which major CPC codes AI patents tend to fall. This is illustrated in Figure 1 where we aggregate to the four-digit level. The most common CPC codes fall under G06, which is "Computing, Calculating, and Counting". In particular, G06K, "Recognition of Data; Presentation of Data; Record Carriers; and Handling Record Carriers" is the most common four-digit CPC code with G06T ("Image Processing") in a somewhat distant second place. Although appearing far less frequently than the G06 codes, technologies under H04 – "Electricity" – are also fairly common. The AI patents seem to be appropriately classified in terms of technological knowledge foundations.

The second, and for our purposes more central, summarization of the AI patents is where they are found in space. To do so, we geo-code inventor addresses to their respective NUTS2 region in Europe. We then construct five-year periods from 1980 to 2013 using the patents' priority year for the time dimension since it measures the earliest date of invention.[5] We find that yearly analysis of knowledge spaces shows little significant change in the underlying network structure, but that larger conceptual trends are more apparent at the five-year period level, something in-line with

[4]This alternative found roughly one-third as many AI patents as the WIPO approach, however this does not alter our fundamental conclusions: AI is concentrated in certain CPC codes and regions, with the major AI producers being those where AI technology is most central to their knowledge space. While we use a combination of keywords and CPC codes to identify AI patents, other identification strategies exist in the literature. Mann and Püttmann (2017) apply a supervised machine learning algorithm (Naïve Bayes) to the text of US patents to sort them into automation and non-automation patents. Haščič et al. (2015) develop an indicator to identify environmentally-related patents, and Arts et al. (2018) use a text matching algorithm to construct an alternative measure of patent similarity.

[5]As the first AI patents we identify were in 1987, our first period runs from 1980 to 1988.

Figure 2: Distribution of AI Patents by Region



(a) All regions (b) 75th percentile

Figure 3: Count of AI Patents by NUTS2 Region (1988 and 2013)

(a) 1988 (b) 2013

earlier studies (Kogler et al., 2017). After mapping regions and periods, we are left with a count of AI patents per region-period.

As illustrated in Figure 2, the distribution of AI patents across regions is highly skewed. As shown in Panel A, most regions do not have any AI patents at all and, of those that do, most have very few. Given that we only have 5,300 patents distributed over 230 regions, this is unsurprising. That said, even within the top quartile of AI patenting regions, Panel B indicates that the distribution remains skewed. Thus, AI patents are very concentrated in a handful of regions with a mere 23 regions accounting for 39.9% of all AI patents.

The concentration of AI patents can also be seen in Figure 3 which compares the accumulated number of AI patents in each NUTS2 region in 1988 and 2013. Year to year changes in the annual number of patents published are illustrated in Figure 4. The first AI patent applications we identify were published in 1987, when seven were published. Following a period of relatively little activity, there was a jump in the annual number of patents in the early 1990s. Around 2010, there was another shift where not only did the number increase, but so did the annual growth rate. This is potentially indicative of the achievement of a critical mass across both time and regions, as Figure 3 shows.

As the above figures indicate, certain regions have emerged as hotbeds for AI innovation. Table 1 lists the top 10% of AI producing regions along with the number of both AI and Non-AI patents they produced during the sample. While large regions containing cities like Paris and Munich top this list, smaller regions such as Mittlefranken (DE) and East Anglia (UK) also appear. Size aside, what sets these regions apart is their disproportionately large shares of expertise in AI-related CPC codes (% AI CPCs). With 230 regions, the average share of these CPC codes is 0.43%. In comparison, the CPC-share of the top five biggest AI producing regions is at least five times larger. This suggests that regions at the forefront of innovation in computing overall are also those with an advantage in producing AI patents.

Figure 4: AI Patents by Year

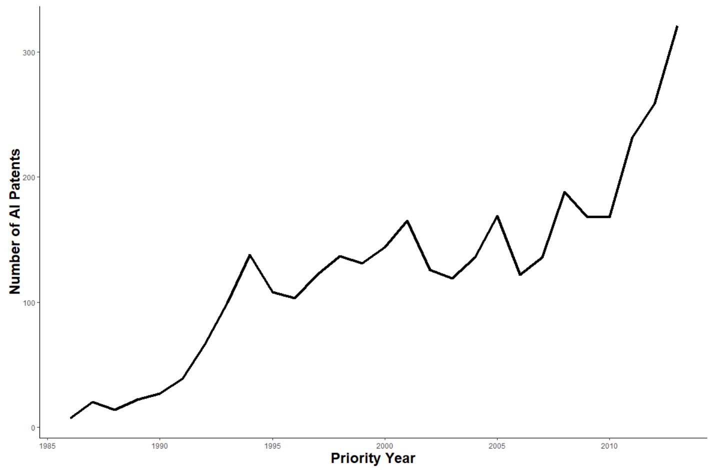
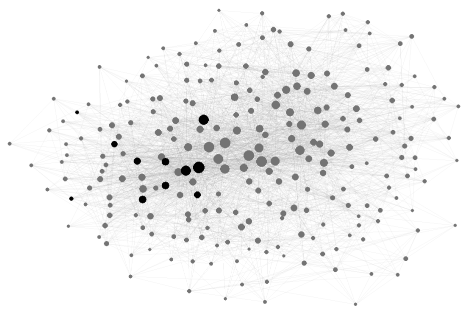


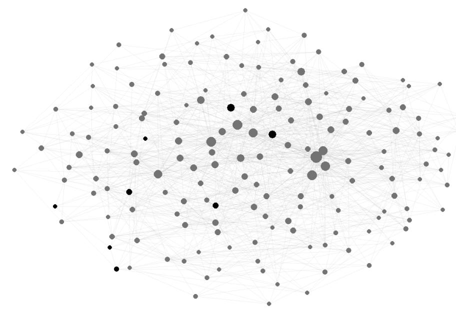
Table 1: Top AI Producing Regions

NUTS 2	Region	AI Patents	Non-AI Patents	% AI CPCs	AICI Change
FR10	Île de France	293	173250	6.93%	2.359
DE21	Oberbayern	280	134106	5.64%	4.852
DE25	Mittlefranken	172	46153	2.25%	0.908
NL41	Noord-Brabant	137	84923	5.45%	1.481
DE11	Stuttgart	120	131917	2.74%	1.303
DE12	Karlsruhe	106	80240	2.57%	0.954
DE71	Darmstadt	77	108034	1.81%	2.420
UKH1	East Anglia	72	28897	1.45%	2.405
DEA2	Köln	72	87022	1.72%	1.186
ITC4	Lombardia	70	66708	1.07%	1.328
DE30	Berlin	68	40251	1.48%	0.804
FR71	Rhône-Alpes	66	78988	1.93%	1.388
DE14	Tübingen	66	44424	1.02%	1.000
DE13	Freiburg	65	51076	1.72%	1.060
SE11	Stockholm	64	40235	2.95%	0.911
UKJ2	Surrey, East and West Sussex	63	21303	1.32%	0.330
DE92	Hannover	60	28012	1.06%	1.274
FR82	Provence-Alpes-Côe d'Azur	54	25405	1.82%	0.689
SE22	South Sweden	52	22225	1.41%	1.018
UKJ1	Berkshire, Buckinghamshire, & Oxfordshire	48	31575	1.41%	0.279
FI1B	Helsinki-Uusimaa	44	34030	2.52%	0.406
DE27	Schwaben	43	28100	0.74%	1.785

Figure 5: Knowledge Space and AI



(a) North Brabant



(b) Veneto

3 AI and the Knowledge Space

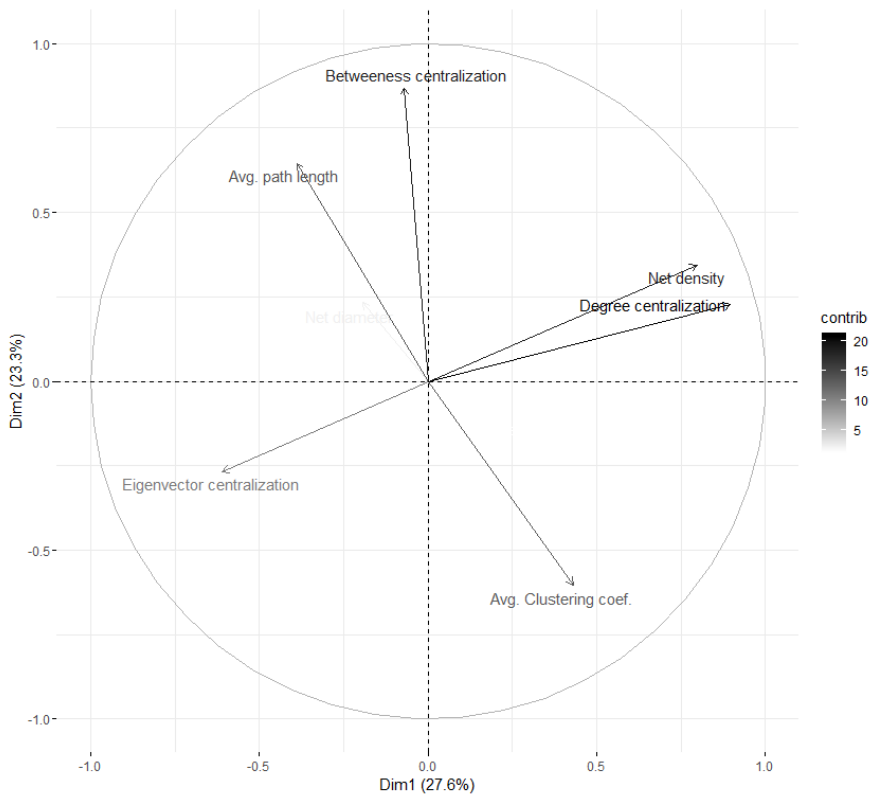
While the above describes the distribution of AI patents, we are also interested in how they connect to a region's innovative environment. This is because many AI-promoting policies specifically seek to develop AI with an eye towards commercial application. We follow Kogler et al. (2013, 2017) and construct the knowledge space for each of the regions and time periods. The knowledge space is often used in the Evolutionary Economic Geography literature to measure patent proximity and regional specialization (Feldman et al., 2015). Succinctly, it represents a network of CPC codes within a region and period. Each CPC code is a node in the network, and each time two CPC codes are listed on the same patent, an edge is created between the two nodes. A network is then created by minimizing the length of edges, with more weight given to the most traversed edges. This region-by-region optimization places the most frequently used and tightly integrated CPCs in the "center" of the knowledge space. Further, it provides a set of network indicators describing the shape and integration of the regional knowledge space.

To be specific, for each knowledge space we construct the following descriptive network variables: a) Number of edges; b) Network density; c) Network diameter; d) Average path length; e) Average clustering coefficient; f) Eigenvector centralization; g) Degree centralization; and h) Betweenness centralization. The number of edges is the count of total edges in the network. If more than one patent contains the same link between nodes, edges are counted more than once. Network density measures the number of actual connections out of the total possible number of connections within a network. Network diameter measures the shortest path that spans the entire network. The average path length measures the average distance between nodes. The average clustering coefficient is the number of three-way node connections or *clusters* out of the total possible number of clusters. Eigenvector centralization is a measure of the average centrality of nodes in a network. Degree centralization is the average number of edges to which any given node is connected. Finally, betweenness centralization measures the number times a node is used as an intermediate step in a path between two nodes. Thus, each measure gives a characteristic of the overall network structure of each region-period's knowledge space.

Figure 5 illustrates two regional knowledge spaces. On the left we have the Dutch region of North Brabant (a significant AI producer) and on the right the Italian region of Veneto (a minor AI producer). The figures were created using a force-directed graph drawing (Kamada-Kawai layout) where the position of the nodes is proportional to graph distance, and the size of the nodes reflects their degree centrality, i.e. their total number of links. While these regions' network structures are similar, they differ in terms of the position and relative importance of AI-related nodes which are the dark black nodes. These nodes are more central, closer to one another, and better connected in the North Brabant knowledge space.

For each NUTS2 region and five year time period we construct two knowledge spaces. In the first, we use all of the region-period's patents. In the second, we create a counterfactual by omitting the AI patents and recalculating the knowledge space's characteristics. Note that we are omitting only the AI patents, not entire CPC codes. Doing so affects the network by reducing the number of connections between CPC nodes, and in some cases may delete CPC nodes entirely if they are not used in Non-AI patents. These changes affect regional knowledge spaces differently depending on how important or central AI is to a given knowledge space. For example, a network in which AI is important will be completely re-optimized in the absence of AI nodes and edges, leading to very different values of the network indicators. Others which either lack AI or for which AI is essentially isolated from other inventive activity will experience little to no change. Using the changes in each of the network characteristics, we then construct the AI centrality index (AICI) using using principal components analysis (PCA) on the network indicators to construct an

Figure 6: Principal Components Analysis of Network Characteristics



equally-weighted, normalized index of changes in the network characteristics. Figure 6 illustrates the weighting of the components. When AI patents are prominent in a knowledge space, their removal will cause a decrease in the level of centralization in the network and create a more dispersed knowledge space. This would then mean a large value of the AICI.

Figure 7 shows a histogram of the average AICI for all regions and all time periods. As with the distribution of AI patents, the distribution of the AICI values is skewed with most region-periods having little to no change. This is to be expected since for most region-periods, we are omitting very few patents. Table 2 gives details on changes in each of the components in the index as well as the total index change (the AICI). When using all regions, the mean AICI across region-periods is 0.564. As just noted, however, this is pulled down by the regions with little to no AI and we therefore also report the changes for the top quantiles (the 75th, 90th, and 95th percentiles respectively) of AI-producing regions. As we focus increasingly on those areas with the most AI patents, the mean AICI grows considerably, mostly due to changes in the number of edges.[6]

[6]Table 1 provides the AICI change for the top AI producing regions.

Figure 7: Histogram of AICI

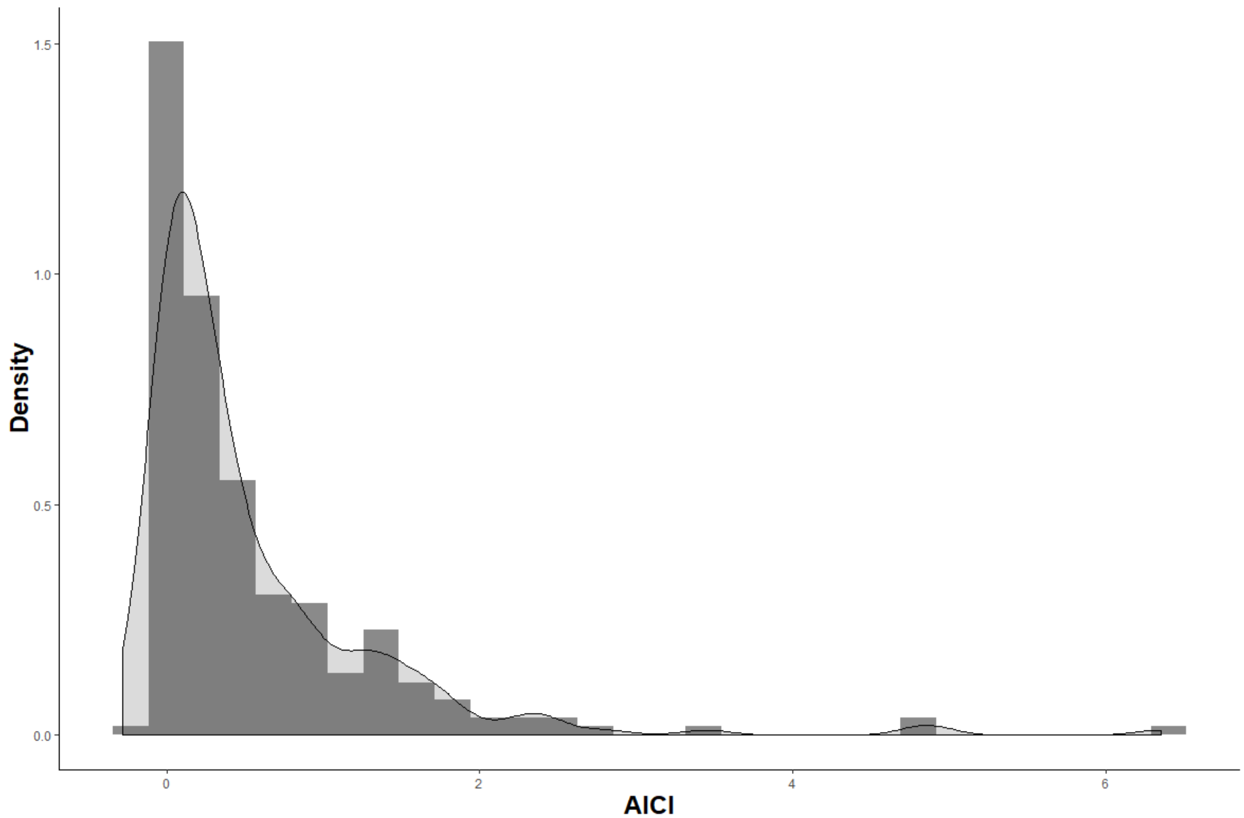


Table 2: Knowledge Space Changes when Omitting AI

Variables	All		75th Percentile		90th Percentile		95th Percentile	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
No. Edge	2.487	2.788	4.540	3.616	6.068	4.073	7.913	4.617
Net Density	−0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Net Diameter	−0.008	0.19	−0.002	0.108	0.012	0.137	−0.019	0.068
Avg. Path Length	0.001	0.027	0.0004	0.020	0.002	0.020	−0.002	0.002
Avg. Clustering coef.	−0.001	0.004	−0.000	0.001	−0.000	0.000	0.000	0.000
Eigenvector centr.	0.001	0.010	−0.000	0.001	−0.000	0.000	−0.000	0.000
Degree centr.	−0.001	0.002	−0.000	0.001	0.000	0.000	0.000	0.000
Betweeness centr.	−0.001	0.004	−0.000	0.001	0.000	0.001	−0.000	0.001
AICI	**0.564**	**0.833**	**1.014**	**1.059**	**1.343**	**0.950**	**1.722**	**1.102**
Obs.	224	224	60	60	24	24	13	13

A different approach is to plot, for the 75th percentile, the number of AI patents (vertical axis) against the AICI (horizontal axis). This is found in Figure 8, where we also plot the estimated trend from a bivariate regression (where the shaded region is the confidence interval). As can be seen, there is a positive correlation, that is, those regions where AI patents are most prevalent are those for which AI is the most central. This points to the possibility that for AI development to succeed, it may be necessary to embed it into a region's overall innovation landscape. As the policies discussed by (Dutton, 2018) often provide incentives for the hand-in-hand development of basic AI and its application, this may well indicate that policy-making is well in line with the findings presented here.

Figure 8: AI Patents and AICI - 75th Percentile

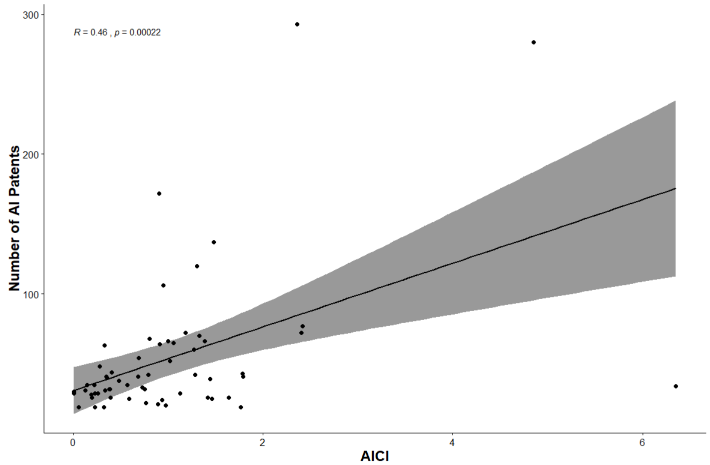
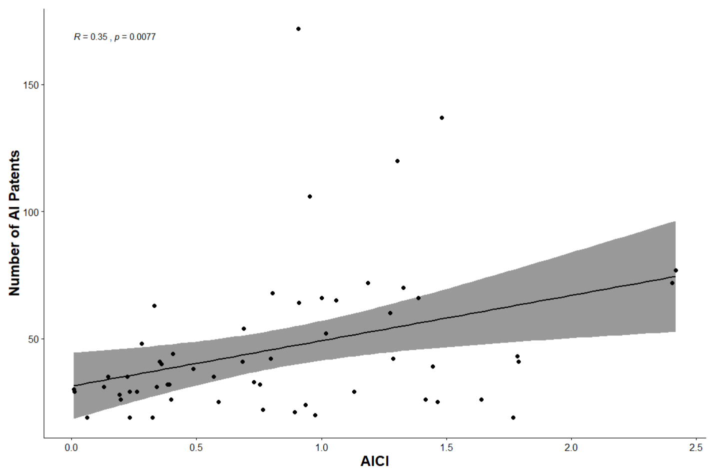


Figure 9: AI Patents and AICI - Outliers Omitted



As a final exploration, one feature visible in Figure 8 is the presence of three outlier regions: ITC1 (Torino), FR10 (Paris), and DE21 (Munich). Therefore in Figure 9 we remove them and re-estimate the correlation. As shown, there is still a clearly positive relationship between the size of the AICI and the number of AI patents showing that, even for moderate AI-producing regions, this correlation holds.

4 Conclusion

AI is clearly one of the buzzwords in contemporary innovation and the rush to develop and market it is palpable. As governments scramble to implement policies to support "Industry 4.0", it becomes increasingly necessary to develop an understanding of how, where, and why AI development is taking place. We contribute to this in three key ways. First, to overcome the lack of CPC codes capturing AI, we use a text matching algorithm to identify AI patents, finding just over 5,300 of them in Europe from 1980-2013. Second, we describe the regions that are most successful in generating AI patents finding that success in computing-related innovation activities likely feeds into success in AI. Finally, we position the AI patents into each region's knowledge space and develop a methodology for describing how embedded AI is in the region's inventive network. When doing so, we find that the AI superstar regions also tend to be those for which AI is most central in its knowledge space. In addition, this contributes methodologically by developing the first approach to measuring how embedded a particular technology is in a local knowledge space.

From a policy perspective, our results suggest two things. First, if AI is best developed by linking it to other technological innovations, our findings support the application-driven AI promotion policies currently in use by many governments. Second, it suggests that those policies alone are unlikely to be successful since a large part of AI-development capabilities build from the historic strengths of a region. Thus, even if ”smart specialization” targets AI, only some regions may be able to achieve their policy goals. In addition, if AI has the economic returns predicted by its supporters, this suggests that as the technology grows it is likely to add to the unequal distribution of income growth across regions. Since our data indicates that the development of AI entered a new, rapid phase of development starting in 2010, such shifts may well already be underway. We therefore hope that our results combined with incoming data can provide a framework for identifying which factors feed into the development of AI and which policies can be used to best capture its opportunities.

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