CHAPTER 14

INNOVATION POLICY FOR A COMPLEX WORLD

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Summary

This chapter examines theoretically and empirically the spatial concentration of innovation in EU regional ecosystems. It proposes a detailed geography of patent distribution in several strategic areas and key technologies such as artificial intelligence (AI), blockchain, quantum computing, batteries, hydrogen, mRNA and oncology diagnostics and treatments, and looks at the complementarities across EU regions. It uses an economic complexity approach and regional network analysis to assess new opportunities for collaboration across EU regions and optimise knowledge sharing to increase the competitiveness of the EU in strategic areas and some key technologies.

1. Introduction

New technologies are invented by a few but change the life of everyone. The development of mRNA vaccines is halting COVID-19 deaths and hospitalisations. Intelligent machines drive cars and read lung scans. They can also predict what we will want to listen to, watch or buy next better than our spouse or lifelong friends. Developing controlled nuclear fusion could solve our energy needs. As Brynjolfsson and McAfee (2014) put it, technological change has bent the curve of human history like nothing else before. But who builds the technologies that get to change everyone's lives? Who decides on the core values and ethical considerations that get embedded into new products? It turns out that one of the most striking features of today's complex world is that innovation is increasingly consumed **globally** while increasingly produced **locally**.

So where does innovation come from? Large cities, mainly. Tokyo, Seoul, San Francisco, Paris and Osaka alone account for more than 20% of all new inventions granted by the European Patent Office (Paunov et al., 2019). This is a staggering number. We know from economic geography and innovation studies that urban environments make it possible to share costly infrastructures, match specialised professionals with cutting-edge organisations and provide multiple learning channels (Duranton and Puga, 2004). There is little doubt that – more than other economic activities – innovation thrives with proximity (Boschma, 2005). But as society evolves and we keep pushing knowledge frontiers, we start noticing a surprising pattern. The most transformative of all scientific and technological fields, such as biotech and IT, are also the most spatially concentrated (Balland et al., 2020).

Although a lot has been written about the spatial concentration of innovation, a large piece of the puzzle is still missing in understanding the big picture and adopting the research and innovation policy we need in today's hyperconnected world. I adopt complex systems thinking to put forward the idea that the massive dual spatial footprint we observe is a reflection of structural features of our world. The main idea of this chapter is that when the world becomes more complex, knowledge consumption becomes more global and knowledge production becomes more local. By complexity, I mean that more and more economic actors are becoming interdependent. This, in turn, creates structures that hide fundamental properties that shape a wide range of socio-economic outcomes (Hidalgo, 2021; Balland et al., 2022).

Linking increasing complexity and spatial concentration has three major implications for research and innovation policy. First, the reality of knowledge concentration requires putting regions and cities at the heart of the innovation strategy of large countries and economic zones. Second, the increasingly global nature of knowledge consumption means that regions compete based on the global value of their products. There is no room for second-best. France and Germany cannot compete with China and the USA, but Europe can. The European system of innovation is a knowledge network of regions. We need to implement an innovation policy that is coherent with this reality and focus on stimulating links between regions to scale high-quality products and accelerate leadership towards climate neutrality and the digital transition. A third implication of this complex world for innovation policy is that it is becoming impossible for political leaders and policymakers to fully understand new technological landscapes and to systematically assess which regional ecosystems are the most valuable for specific technologies. We need new tools. I will introduce how graph-based machine learning (GBML) can complement human intelligence to design sound policy in a complex world.

In section 2, I will discuss the theoretical foundation of why innovation concentrates in a complex world. In section 3, I will provide empirical evidence on the spatial concentration of innovation in EU regional ecosystems. Section 4 will focus on how to leverage regional ecosystems with human and artificial intelligence. Section 5 will show how this recommender system can be used to assess potential new opportunities in key technologies such as AI, blockchain, quantum computing, batteries, hydrogen, mRNA and oncology diagnostics and treatments. Section 6 will conclude and summarise key implications for research and innovation policy.

2. Why a more complex world accelerates the concentration of innovation

If you had asked prominent economists, policymakers or business executives at the dawn of the internet, few would have predicted the merciless monopoly of digital giants such as Google, Amazon, Netflix, Alibaba or Tencent. Digital technologies were supposed to flatten the world. Everyone, everywhere, would get a chance to collaborate and create technologies consumed on the other side of the planet. This vision turned out to be dramatically wrong. Today's reality is that innovation is increasingly consumed globally while at the same time increasingly produced locally. Most of the rich Western world consumes Gmail or Netflix products on a daily basis, but the AI that powers their technology only comes from tiny pockets within Silicon Valley, Seattle or Boston. Geography matters less and less on the demand side but more and more on the supply side. This is the worst-case scenario for spatial inequality[1]. As the global consumer base widens, it fuels the growth of a few local peaks of Richard Florida's spiky world. The wider the base, the higher the peaks. Paradoxically, a more global world has also much more marked regional features (Storper, 1997).

Why does spatial inequality emerge as a result of the increasing complexity of our world? Let us first examine global demand. Digital technologies and falling transportation costs of physical goods allow products to be widely distributed. That means that it matters less and less where consumers are located – global corporations can access everyone's wallets. Global competition is emerging in more and more industries. This is completely different from non-tradable industries such as the hairdressing business. A hairdresser in Kraków does not compete with a hairdresser in Porto, even it provides a much better and cheaper service. But customers in a global, interconnected world do not care about the second best because they can access all providers equally. Email services, for instance, do compete globally. Gmail has 1.5 billion active users worldwide, Outlook about 400 million, Yahoo, 200 million. This is an incredibly skewed distribution, where the winner takes all and the rest eat the crumbs.

So the fact that our world is incredibly interconnected allows for the possibility for the few winners to take it all. Things get even worse when the quality of the product depends on data collection. A small initial comparative advantage can quickly compound into an absolute monopoly. Slightly better initial recommendations of an AI system will attract more users. More users will automatically lead to more data for the digital platform. What comes next is that more data will lead to better predictions and therefore more users, and that this self-reinforcing feedback loop will not stop until a specific segment of the digital market is almost entirely absorbed by a handful of global giant organisations (Lee, 2018; Tucker, 2019; Catalini and Gans, 2020; Aral, 2021). Google has a monopoly of website recommendations in the West and Baidu in China; Amazon in product recommendations in the West; Alibaba in China. The logic is the same for other digital products[2].

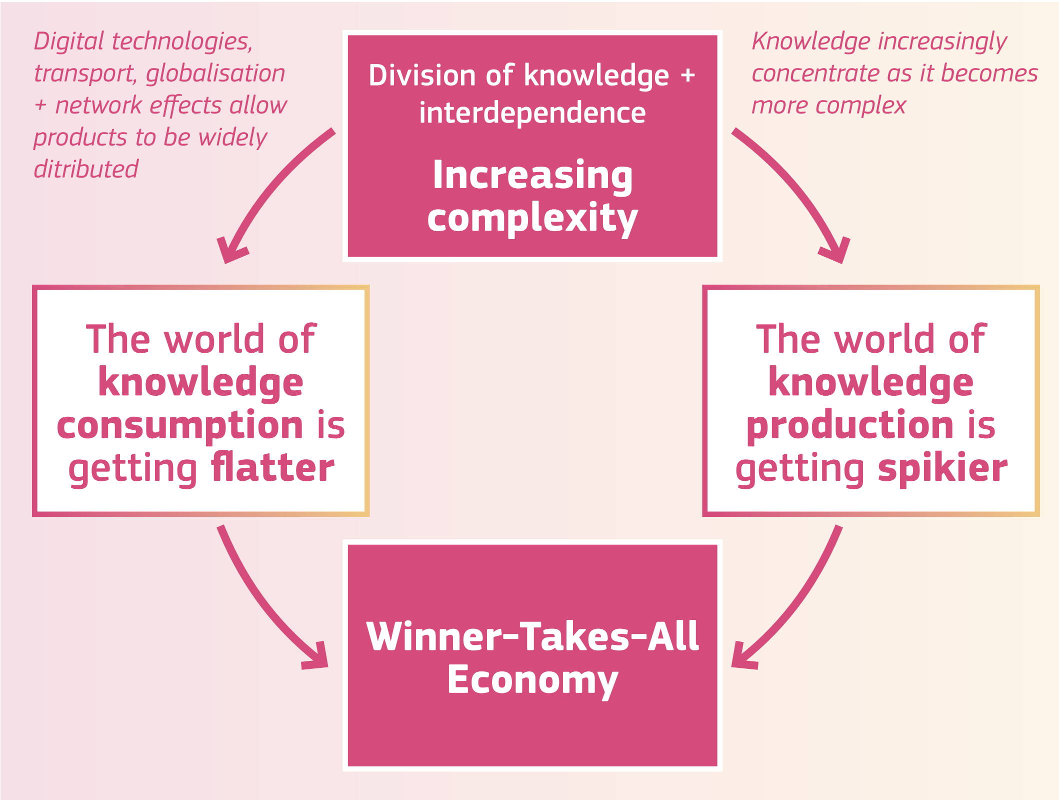
1 Spatial inequality has been documented to be on the rise across the world and to fuel populism and social unrest (Rodríguez-Pose, 2018). More complex and interdependent economic structures create the leverage conditions that condition the rise of inequality within and between regions.

2 It is a feature of Web 2.0 and is predicted to be disrupted by blockchain technologies, decentralisation and the evolution towards Web 3.0.

So far, we have discussed why the structural features of our world create the possibility for superstars entrepreneurs, products and corporations to emerge. It would not be too much of a problem if these winners of the global economy were also distributed randomly in the world. The problem is that they also concentrate in a few places. Digital goods are highly complex activities that concentrate in large cities, the knowledge hubs of the global economy (Balland et al., 2020). Complex products require a deeper division of knowledge, which forces individuals to narrow down their expertise and specialise (Jones, 2009). In fact, there is a limit to how much knowledge can be stored in someone's head (Hidalgo, 2015). This division of knowledge creates high coordination costs since specialised knowledge alone is useless. It needs to be connected back to other specialised individuals, which is why we have witnessed an increasing size of teams in science and innovation (Wuchty et al., 2007). Cities – in particular, the largest ones – help to solve the coordination problems created by the division of knowledge by creating multiple mixing and matching opportunities.

The rise of the winner-takes-all economy results in increasing complexity, a more global world of knowledge consumption and a more local world of knowledge production, as summarised in Figure 1. The magnitude of this monopolistic structure in strategic products and technologies shapes the spatial nature of innovation, which we will document in the next section. These patterns call for new principles of innovation policy and new tools.

Figure 14-1: **The rise of the winner-takes-all economy**



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3. Regions are the engines of the European innovation system

The most accepted approach to systematically assessing the spatial distribution of new technologies is to analyse patent documents. Even though patented inventions do not capture all forms of invention and knowledge production, they contain unique information that has been extensively used in innovation studies[3] (Jaffe et al., 1993; Audretsch and Feldman, 1996; Hall et al., 2001; Thompson and Fox-Kean, 2005). In exchange for the codification of and openness in how technology is produced, patent offices over the world grant the right to exclude others from the commercial exploitation of the invention. This allows the systematic documentation of new technologies that no other form of data allows.

Two key pieces of information are available in patent documents to map innovation ecosystems accurately and systematically and to further inform innovation policy: what is invented and where it comes from. Both pieces of information are available at a very fine-grained resolution. The place of residence of inventors gives the detailed geography of inventions, while each patent is meticulously classified within 250 000 technological categories (international patent classification, IPC). Combining these two key pieces of information allows us to map the geography of innovation in Europe precisely. In this chapter, I use the OECD REGPAT 2021 database (Maraut et al., 2008). The REGPAT dataset provides detailed information on patents filed at the European Patent Office (EPO) and at the World Intellectual Property Organization (WIPO) since 1978.

What does the geography of innovation look like in Europe? Figure 2[4] simply maps the number of patents per capita in information and communication technologies during the period 2014-2018[5]. What is clear from this map is the strong evidence of spatial concentration of inventive activities, as also extensively shown in part I of this report (Section 2.2 – Zoom in – Regional analysis). The European information and communications technology (ICT) innovation system is formed by leading regions Stockholm, South Sweden, Helsinki-Uusimaa, Mittelfranken, Oberbayern, North Brabant, Brittany and Île de France. Île de France, Oberbayern, Stockholm, Mittelfranken and Brittany are also the top five regions in terms of the absolute number of ICT patents, and together account for no less than 30 % of the ICT patents of the EU-27 regions. These leading regions are key to establishing the global sovereignty of EU technologies. But what is also fascinating in this map is that country borders are almost impossible to distinguish. European regions, not countries, are where innovation truly concentrates and therefore should be the focus of innovation policy.

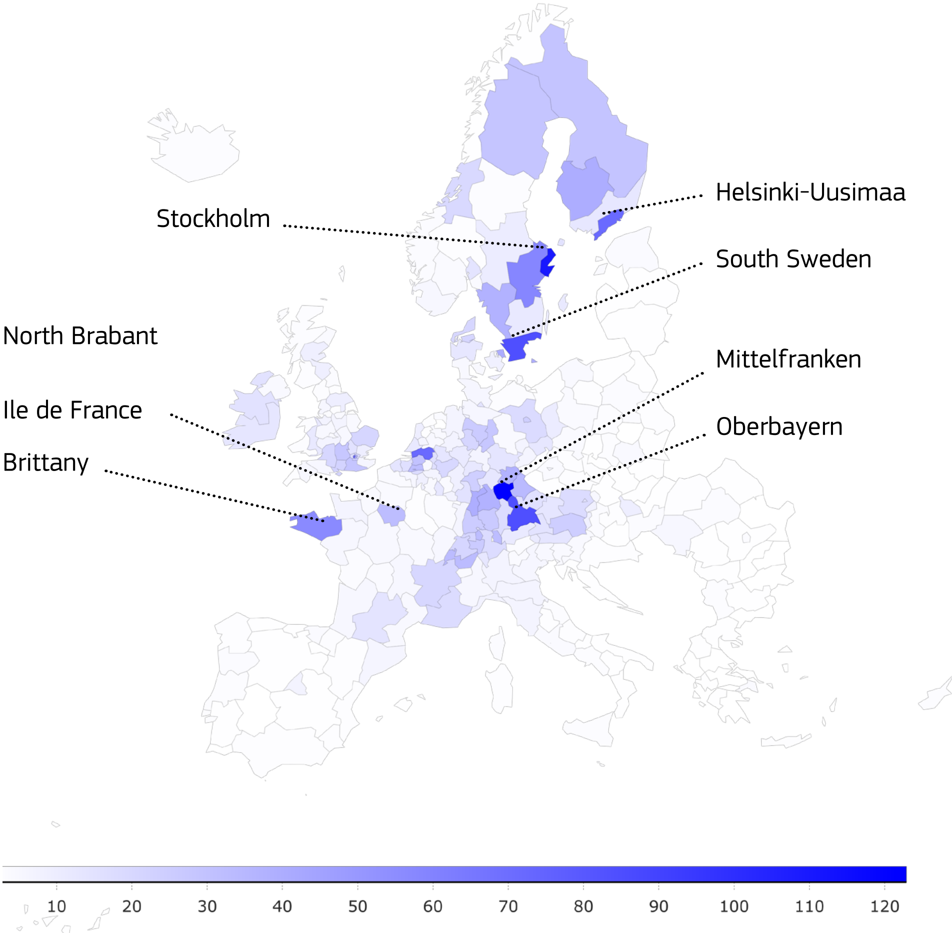
This concentration pattern becomes even stronger when we unpack the level of complexity of technologies. This distinction is not trivial because complex technologies are the ones that allow for the most leverage of economic structures and therefore the ones that are the most critical for future economic growth (Hidalgo and Hausmann, 2009; Hidalgo, 2021; Balland et al., 2022). As mentioned earlier, complexity refers to the division of knowledge behind the creation of a specific technology.

3 The geography of innovation can also be analysed using participation in R&D projects, venture-capital deals (Crunchbase, DealRoom) or GitHub repositories for instance.

4 An interactive version of this map is available here: https://www.paballand.com/asg/srip/map-ict-pc.html

5 This map uses data from Balland and Boschma (2021).

Figure 14-2: ICT regional ecosystems in Europe



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A technology that a human can invent entirely by herself is, by our definition, simple. Now, the more you build on others' knowledge, skills and inputs, the more complex the technology is. A technology that involves many actors interlinked in very specific ways is more complex. There are many ways to measure complexity (Fleming and Sorenson, 2001; Hidalgo, 2021) but in this paper, we use the standard eigenvector reformulation initially proposed by Hidalgo and Hausmann (2009) for traded products and recently adapted for patent data by Balland and Rigby (2017). This method is purely outcome-based. It brings together the diversity of regions and the ubiquity of technologies they produce to identify the technologies that a lot of regions would like to produce but very few can.

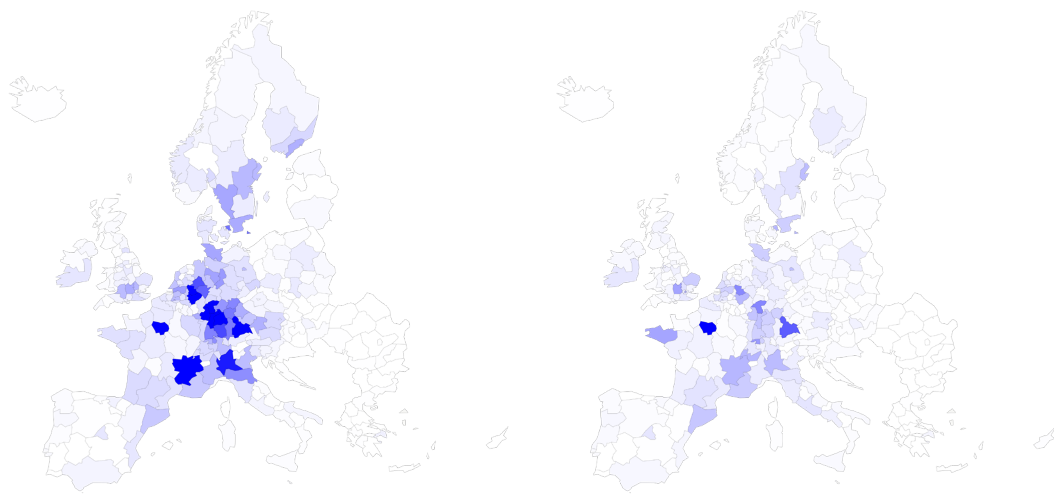
Figure 3 maps the geography of complex and non-complex patents in European regions from 2015 to 2020[6]. On the left panel, we can see the distribution of the least complex patents[7] (bottom 25 %) and on the right, the most com-

6 For an extensive analysis of the geography of knowledge complexity in Europe, see Pintar and Scherngell (2021)

7 An interactive version of this map is available here: https://www.paballand.com/asg/srip/bottom25.html

Figure 14-3: The geography of complex patents in Europe

Bottom 25 % complex patents **Top 25 % complex patents**



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plex ones[8] (top 25 %). We can see two very different geographies. Complex patents are very highly concentrated while the least complex ones are much more dispersed across European regions. The regions that have a disproportionate number of complex patents are mainly the capital regions such as Île de France, Inner London, Stockholm or Madrid.

To systematically document the unequal distribution of technologies we turn to a simple index of spatial concentration: the Gini coefficient. The Gini coefficient is defined as a ratio of two surfaces derived from the Lorenz curve and ranges from 0 (perfect spatial equality where every region produces the same number of patents) to 1 (perfect spatial inequality where one region produces all patents).

In Figure 4, I analyse, for 2015-2020, the spatial inequality behind the production of 35 core technologies[9] as originally defined by Schmoch (2008), together with seven key technologies for European technological sovereignty: AI, blockchain, quantum computing, batteries, hydrogen, mRNA and Oncology[10].

8 An interactive version of this map is available here: https://www.paballand.com/asg/srip/top25.html

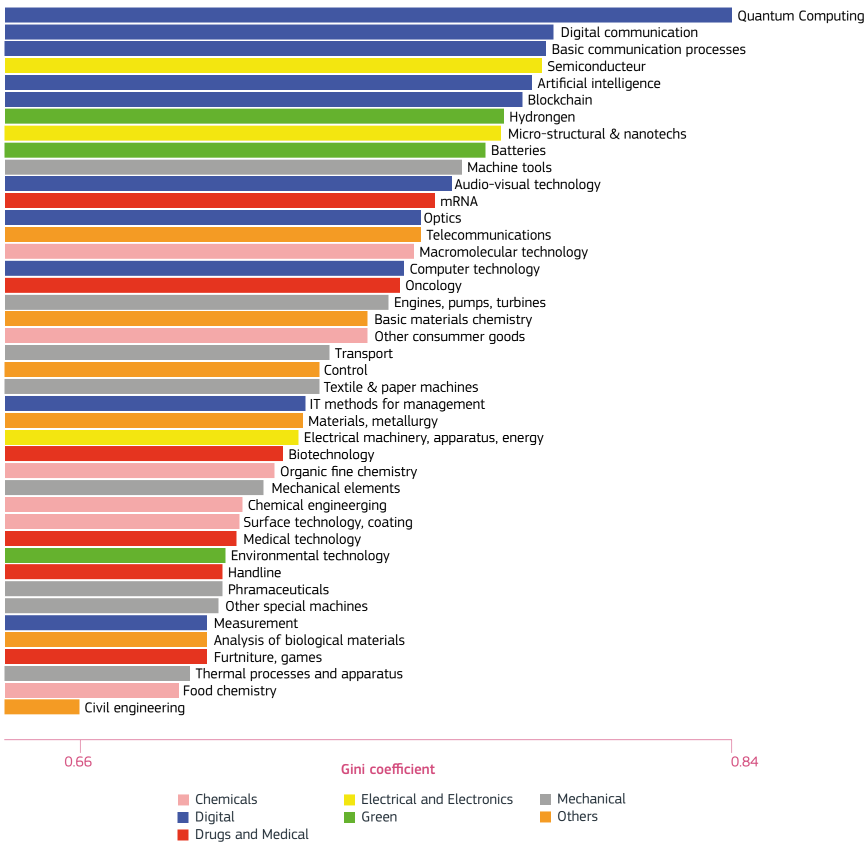
9 The analysis of biological materials; audio-visual technology; basic communication processes; basic materials chemistry; biotechnology; chemical engineering; civil engineering; computer technology; controls; digital communications; electrical machinery, apparatus, energy; engines, pumps, turbines; environmental technology; food chemistry; furniture, games; handling; IT methods for management; machine tools; macromolecular chemistry, polymers; materials, metallurgy; measurement; mechanical elements; medical technology; micro-structural and nanotechnology; optics; organic fine chemistry; other consumer goods; other special machines; pharmaceuticals; semiconductors; surface technology, coatings; telecommunications; textile and paper machines; thermal processes and apparatus; transport. These technologies are defined from the updated Cooperative Patent Classification (CPC) classification proposed in Schmoch (2008).

10 The technologies are identified from text mining patent documents and the CPC classification, following the method of Balland and Boschma (2021).

The five most concentrated fields are quantum computing, digital communication, basic communication processes, semiconductors and AI. These are also highly complex fields that are associated with high talent pools and capital investments. The five most spatially dispersed fields, however, are less knowledge-intensive activities: civil engineering, food chemistry, thermal processes and apparatus, furniture and games, and analysis of biological materials. Again, from this exercise, it is clear that the most complex fields are also the most spatially concentrated.

Another fundamental way to document the spatial distribution of knowledge is not to look at regions in isolation from each other but to analyse the European interregional system of innovation. In Figure 5, we plot the co-inventor ties between regions[11], for all technologies. The results are striking. When looking at collaborations, country borders become extremely marked. The top 10 connections of Île de France – the EU regions with the most internal collaborations – are all other French regions.

Figure 14-4: Spatial concentration of core technologies



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11 In the network presented in Figure 4, we only display links between regions (n=74) that have more than 10 000 internal links. This is purely for visualisation purposes. We also use a maximum spanning-tree algorithm to map the backbone of the network and to avoid isolated nodes. Some primary links are therefore removed for visualisation purposes. The results are qualitatively similar when plotting the whole network of European regions. An interactive version of this map is available here: https://ec.europa.eu/assets/rtd/srip/2022/figure-14-4.xlsx

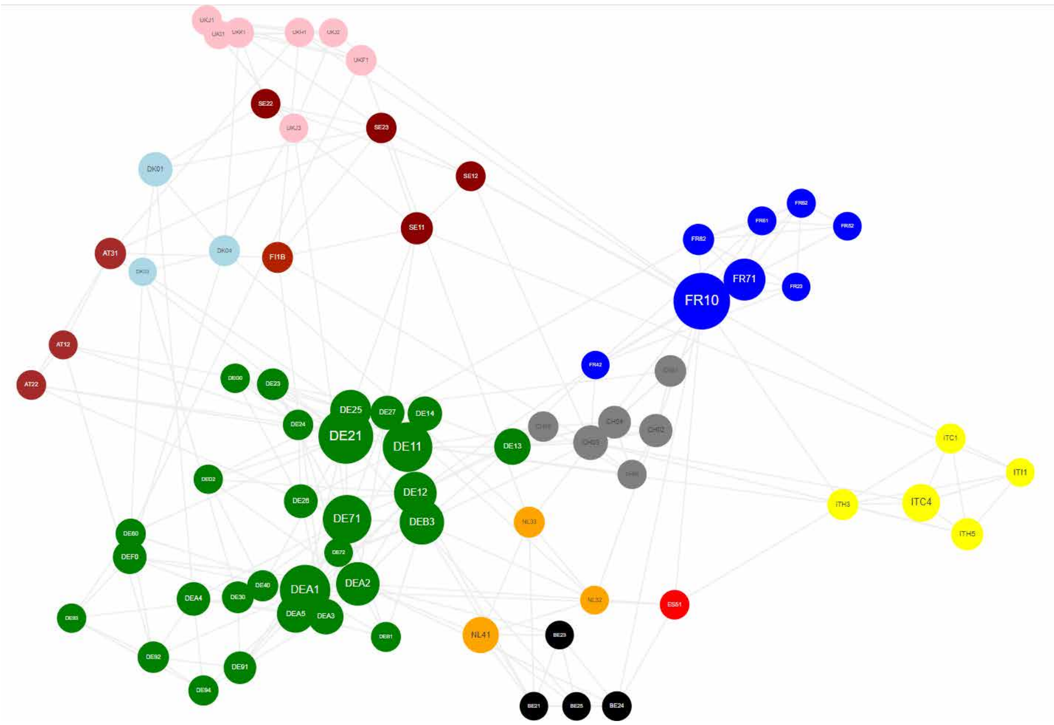
The same goes for Upper Bavaria and other EU regions. European regions disproportionally favour same-country collaborations over pan-European ones. Based on the maps presented in Figures 2 and 3, we would expect the top EU regions to be strongly connected. This fact that they are not signals a system failure in the innovation systems that justifies higher-policy-level intervention to scale up EU technologies and achieve global leadership in the twin transition.

We have learned two key facts about the geography of innovation in Europe. First, technologies – especially the most complex ones – are heavily concentrated in a few regional ecosystems. It is essential to take into account this real-world pattern and to design an EU-wide place-based[12] innovation policy. Second, the EU regional innovation system does not reflect this geography when it comes to interregional collaborations.

This gap signals a poor knowledge-capability matching that urgently needs to be reduced with the right network-based innovation policy tools. In the next section, we turn to the use of modern graph-based machine learning tools to:

- identify promising knowledge ecosystems;
- identify the most valuable interregional connections.

Figure 14-5: The EU regional system of innovation



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12 Place-based policy is often meant as policy that helps lagging regions to catch up (Barca et al., 2009). Here, we mean place-based innovation policy in the sense of policy that leverages regional ecosystems to generate EU global leadership.

4. Leveraging regional ecosystems with human and artificial intelligence

A large part of successful innovation policy at the scale of large integrated markets such as Europe, the USA or China comes down to simultaneously betting on the right technologies and the right places. Prioritising investments is key to accelerating global leadership towards climate neutrality and digital transitions while developing EU sovereignty in key technologies. Shall we mainly fund AI? Blockchain? Nuclear power? Solar energy? And how much should go to each technology? Once the overall plan is defined at the level of large countries or economic zones (EU, USA, China) the next important step is to define who receives the funding (regions and cities). This is also critical to enabling diversification of regions and stimulating their long-term economic development (Boschma, 2018; Hidalgo et al., 2018).

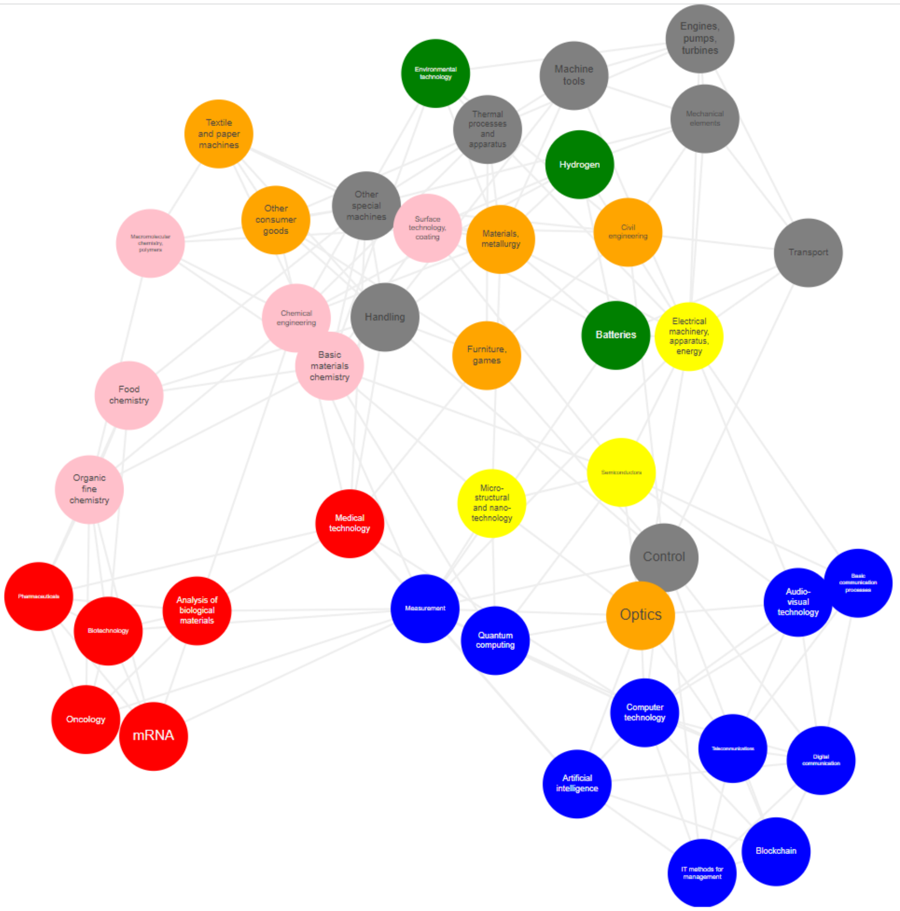
But simultaneously betting on the right technologies and the right places is an increasingly difficult exercise. It was already challenging in a less globalised world characterised by slower technological change but today, there are too many new complex technologies and global knowledge ecosystems to assess intuitively what the optimal investment really is (Balland et al., 2019). If the goal is to achieve EU leadership in AI for instance, is it wiser to focus investments on the Île de France, Bavaria and Budapest ecosystems or Milan, Bucharest and Eindhoven? These choices matter tremendously. Domain experts provide very valuable knowledge but cannot have equal knowledge of all new technologies and their geographies. It is getting harder and harder to flag risky strategies and identify hidden gems. We need better tools.

I argue that modern R&I policymaking needs to combine human and artificial intelligence to deliver more optimal public investments. The foundational principles of such AI tools already exist in GBML. Collaborative filtering, in particular, has shown that there is much more predictive power in economic and social structures than in demographic variables. To put it simply, gender, height, country of origin and other individual-level variables are poor predictors of music tastes or purchasing patterns. But it is possible to automate predictions (filtering) by also analysing preferences from many other users (collaborating).

Similar algorithmic principles that govern Amazon, Netflix or Spotify prediction machines can also be applied to the prioritisation of public investment decisions in research and innovation policy. These tools are increasingly applied in the context of the smart specialisation strategy and green policy initiatives (Balland et al., 2019; Balland et al., 2021; Deegan et al., 2021; Mealy and Teytelboym, 2020; Uyarra et al., 2020; Montresor and Quatraro, 2020; Hassink and Gong, 2019) by building on decades-long academic literature on economic complexity and economic geography. One of the key findings of this literature is that regional diversification happens through the principle of relatedness (Hidalgo et al., 2007; Hidalgo et al., 2018). Regions develop new products and technologies by recombining pre-existing available capabilities. Mapping existing capabilities in a region allow estimating the distance with any new domain, measured by the concept of relatedness density.

The particular way technologies are connected to each other indicates how easy it is for a region, country or individual to move from one to the other. It represents hidden constraints that shape our decisions and opportunities. Figure 6[13] is a graph-based representation of how the 42 technologies presented in section 3 are related to each other from 2015 to 2020. Previous research has mapped connections between products (Hidalgo et al., 2007), scientific fields (Boschma et al., 2014) or job categories (Farinha et al., 2019). Here, we use a recombination of subtechnologies on the same patents to produce this graph. We can see how the digital technologies (blue) of blockchain, AI or quantum computing cluster together, while health-related technologies (red) such as mRNA or oncology diagnostics and treatments are grouped in a different quadrant of this space. A fine-grained resolution of this technology space (we can go up to 250 000 technologies) allows mapping of the regional ecosystems that are the most promising for specific technologies.

Figure 14-6: **The technology space**



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13 An interactive version of this map is available here: https://www.paballand.com/asg/srip/tech-space.html

By mapping links between technologies and the current knowledge structure of EU regional ecosystems, it becomes possible to compute relatedness density and predict the growth potential of new technologies. This is a huge breakthrough because it means that we do not need a place to produce knowledge to actually know if it can produce knowledge in the future. Relatedness density indicates – for any domain – the shares of related technologies that are present in a region. To illustrate this principle with a simplified example, let us say that 10 technologies are related to AI and eight of these technologies can be found in Paris. The relatedness density between AI and Paris is 8/10 = 80%. Regions with the highest relatedness density are the strongest candidates for prioritising funding.

Figure 7 presents relatedness density maps[14] that indicate which EU regions are in the best position to lead technological change in seven key technologies. We can see that each technology is characterised by a very specific geography. Île de France, Oberbayern and London have core technologies related to AI but when it comes to batteries, Rhone-Alpes, Stuttgart or Trondelag (Norway) are better positioned. mRNA connects most to technologies found in the capital region of Denmark, in Berkshire, Buckinghamshire and Oxfordshire or in Languedoc-Roussillon.

By plotting relatedness density against a regional variable, it is possible to introduce more nuanced and realistic trade-offs that are fundamental to real-world policymaking. Relatedness density is a region-technology-level variable, so a region can have a high level of relatedness density around a given technology (AI), but very low around another one (biotech). The regional variable would be, by definition, fixed across regions. For illustration purposes, we will discuss regional complexity, which is a predictor of long-run regional development, but it could also be GDP or patents per capita.

Figure 8 presents a framework that indicates the position of all EU regions in terms of their relatedness density around a specific technology (let us say AI, along the x-axis) and the overall regional complexity of the region (y-axis). On the top-right quadrant (**excellence policy**) we have world-class regions (complex) that are also in the best position to become leaders in AI. These are safe bets, but they come with the potential drawback of making strong regions even stronger. The bottom-right corner (**inclusive policy**) shows regions that might not come as quickly to mind but that have strong potential in this technology. Betting on these regions comes with the added benefit of reducing disparities. The two other quadrants do not make as much sense from a structural approach.

14 All relatedness density maps are available as interactive HTML files: https://www.paballand.com/asg/srip/maps/artificial-intelligence.html
https://www.paballand.com/asg/srip/maps/batteries.htmlhttps://www.paballand.com/asg/srip/maps/blockchain.html
https://www.paballand.com/asg/srip/maps/hydrogen.html
https://www.paballand.com/asg/srip/maps/mrna.html
https://www.paballand.com/asg/srip/maps/oncology.html
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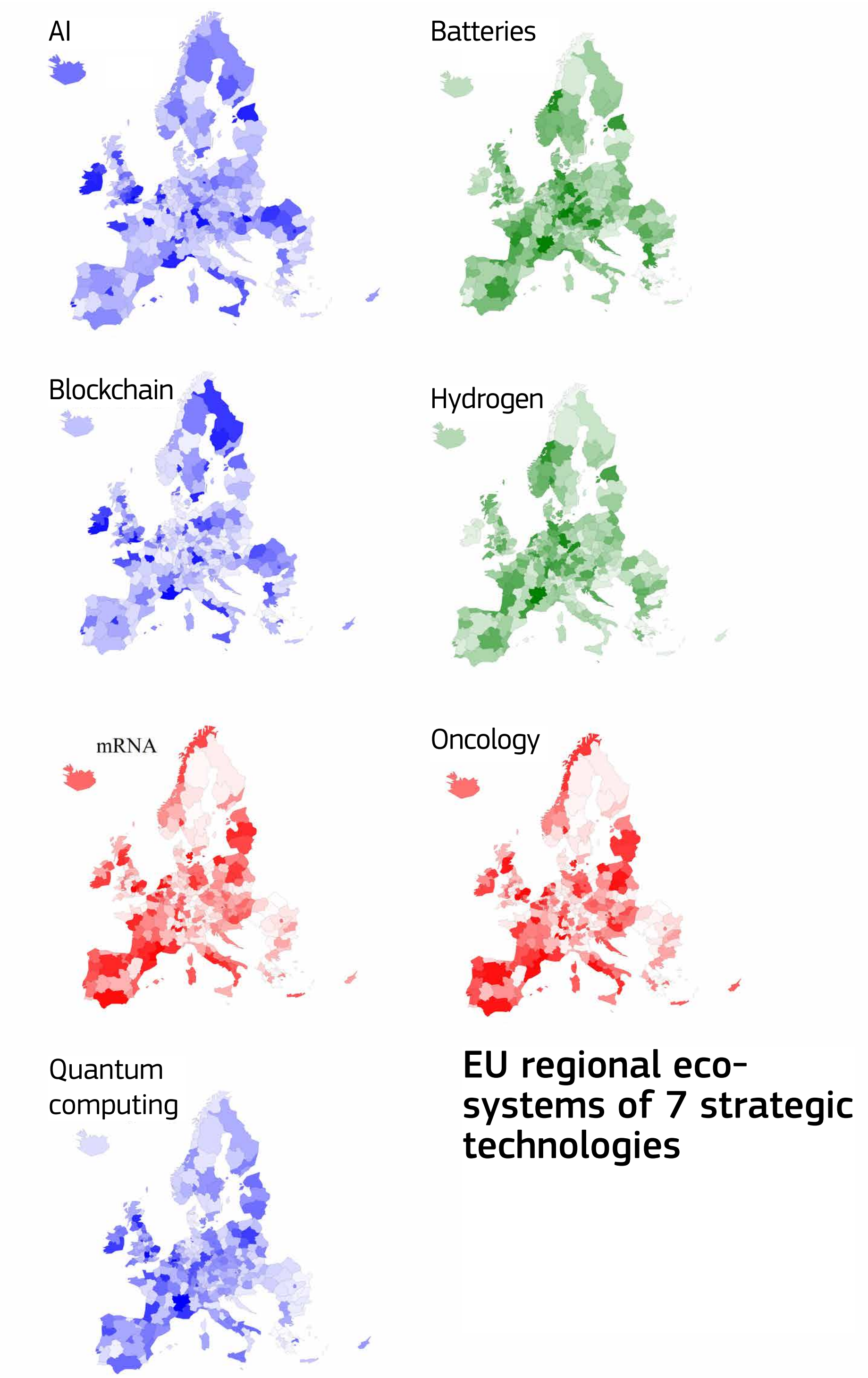
Figure 14-7: Relatedness density maps



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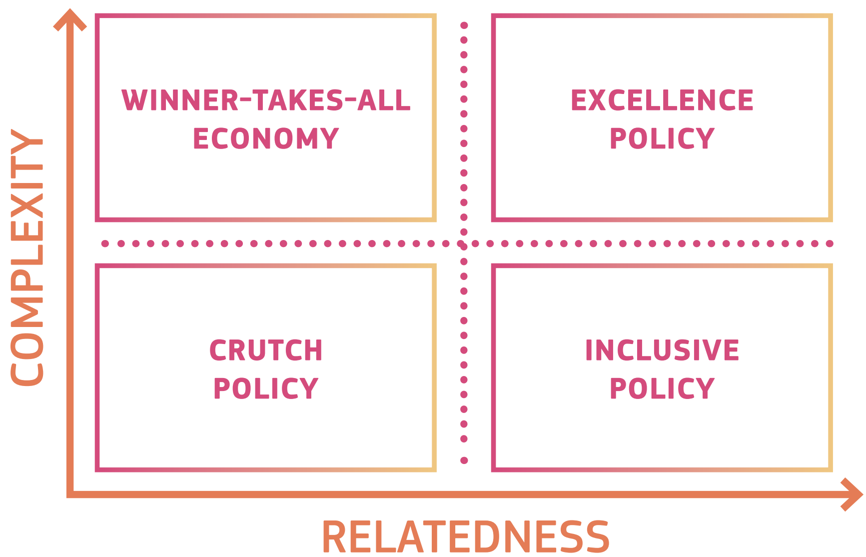
The top-left (**winner-takes-all policy)** indicates regions that are already very strong (overall) and do not have a specific edge in AI. Talent, regional brand, pre-existing capital or infrastructure can explain such an investment. The bottom-left (**crutch policy**) is also to be avoided as it is very unlikely that the support can ever kick-start organic growth in these regions. It does not mean that these regions should be left behind. But from an innovation policy perspective, these regions should focus on technologies in which they have related capabilities.

A carefully designed R&I policy should be technology-specific and empower relevant knowledge ecosystems. It is also important to stimulate interregional linkages. Links that are the most impactful for regional leadership and innovation are the ones that build on complementary assets (Balland and Boschma, 2021). And as shown in section 3, European regions seem to disproportionally favour within-country collaboration. To stimulate pan-European collaboration, we need a strong innovation policy framework that brings European regions together.

Balland and Boschma's (2021) measure analyses gaps and similarities between technology spaces of all EU regions. It is always region-tech-region specific (three-way). With this method, it is possible to assess the complementarity potential of a given region with any other region in a given technology. Let us, for instance, evaluate the complementarity potentials of EU regions with the Occitanie region in the field of AI (as indicated in Figure 9[15]). To put it simply, let us say that AI is related to 100 other technologies (in a more fine-grained version of the overall technology space presented in Figure 6). Occitanie has expertise in 30 out of these 100 technologies, leading to a level of relatedness density between Budapest and

Figure 14-8: **Prioritising investments in regional ecosystems**



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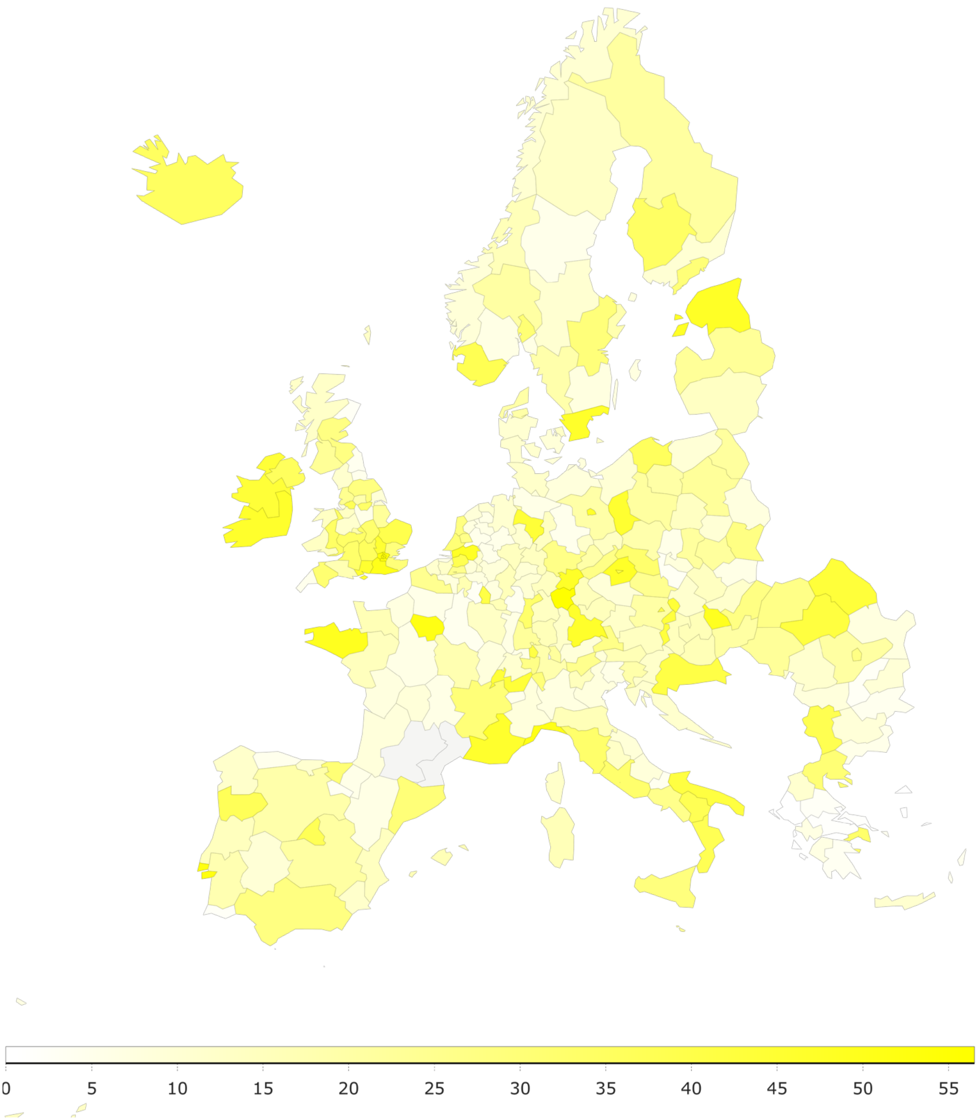
15 An interactive version of this map is available here: https://www.paballand.com/asg/srip/ai-occitanie.html

AI of 50 % (as presented in Figure 7 and in the x-axis of Figure 8). Analysing the portfolio of other EU regions reveals that Budapest has expertise in 49 other technologies that are related to AI but that Occitanie does not have expertise in. Linking to Budapest, Occitanie could compensate for the lack of regional knowledge, and relatedness density would go up by 49 %. This 49 % is the level of complementarity between Occitanie and Budapest in AI. Please note that it would change for biotech or any other technologies and is also not symmetric. If Occitanie only has technology that Budapest already has, then the complementarity score between Budapest and Occitanie in AI would be exactly 0 %.

Figure 14-9: Complementarity maps between Occitanie and other EU regions in AI



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6. Conclusion

The overarching idea of this chapter is that new technologies are extremely concentrated in space. I argue that this spatial concentration is increasing over time as a result of the increasing complexity and interconnectivity of our economic system. I discuss the theoretical mechanisms but also empirically demonstrate that this is especially true for the most transformative technologies, such as AI, blockchain or advanced clean technologies. A few regional knowledge ecosystems are responsible for most innovations that shake the world and impact the lives of all citizens. The most important implication of this real-world pattern is that – more than ever – we need an ambitious innovation policy that truly leverages the spatial dimension of innovation.

To develop such a region-based innovation policy we need tools. I also argue that today's science and technology world is far too complex for policymakers and key stakeholders at the EU, regional or national level to systematically map knowledge ecosystems and the links between them. GBML, the technology behind the recommendation systems of Amazon, Netflix and Spotify, can be used to support innovation policy and public-investment decisions. I show how GBML can map current structures, predict future development paths and also predict best matches between regions based on systemic complementarity analyses.

Beyond understanding key principles and patterns of the geography of innovation, we also need new policy frameworks and instruments. We need to support local governments in setting up ambitious science and technology visions, orchestrating local ecosystems, attracting external players and connecting the dots between local stakeholders. The type of policy instruments chosen could connect to the current smart specialisation policy of DG REGIO. This makes a lot of sense since the seminal smart specialisation concepts outlined by Foray, David and Hall (2009) were developed as an innovation policy and discussed extensively within DG RTD. Today, the smart specialisation strategy is a place-based policy (Barca et al., 2012) in the sense of reducing EU regional disparities by supporting regional change. This is an excellent initiative that is becoming increasingly armed with advanced methodological tools. We need similar instruments with a very different goal. We need a place-based innovation policy that has the clear objective of pushing further overall EU technological sovereignty by betting on the regional ecosystems that are the fittest to achieve global leadership. Regions – not projects – could therefore receive funding based on an overall excellence- and knowledge-matching strategy. It would all be about prioritising technologies to invest in and outlining an execution plan on how to make it happen.

But to truly develop EU sovereignty in strategic technologies, a higher level of leadership is needed. The consequence of the global consumption of knowledge is that we need scale to develop tech champions, especially in the digital sector. The EU has all it takes to compete with China and the USA, but France or Germany cannot go alone. The EU needs to be the captain, setting up overall innovation strategy and building on a system of regions to make it work. But what is clear from the analysis of interregional linkages presented in this paper is that the EU system of innovation is far from being optimally structured. There are an excessive number of within-country collaborations and we are far from a true common innovation area. While one would expect the larger regions or those with the most complementary structures to be the most connected (as is the case in the USA and China), this strong country-border effect considerably harms EU innovation potential.

To thrive in the 21st century, we need strong EU leadership in priority-setting and coordination efforts. Attracting global talent and granting EU-wide special visas, for instance, would not only be a way to boost innovation but also to break a shared historical context that prevents cross-country connections. More directly, we need instruments that build a true European community by encouraging mobility (in the spirit of the Erasmus programme and the framework programmes). What we need is a true Airbus moment, where the division of knowledge at the level of EU regions allows us to scale and develop globally competitive complex products.

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