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Relatedness, Cross-relatedness and Regional Innovation Specializations: An Analysis of Technology, Design, and Market Activities in Europe and the US

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abstract

This article examines how regions develop new innovation specializations, covering different activities in the whole process from technological invention to commercialization. We develop a conceptual framework anchored in two building blocks: first, the conceptualization of innovation as a process spanning technology, design, and market activities; second, the application and extension of the principle of relatedness to understand developments within and between the different innovation activities. We offer an empirical investigation where we operationalize the different innovation activities using three intellectual property rights: patents, industrial designs, and trademarks. We provide two separate analyses of how relatedness and cross-relatedness matter for the emergence of new specializations: for 259 NUTS-2 European regions and for 363 metropolitan statistical areas of the US. While relatedness is significantly associated with new regional specializations for all three innovation activities, cross-relatedness between activities also plays a significant role. Our study has important policy implications for developing and monitoring smart specialization regional strategies.

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How innovation unfolds in space and over time is a critical question in understanding the ways in which regions can reconfigure their activities and thrive (Feldman 1994). However, what is innovation? Schumpeter (1934) stresses that invention is not yet innovation: much needs to happen before a novel idea turns into an actual new product or process that can generate value for users and producers alike. Nevertheless, most conceptual and empirical research on the geography of innovation has examined upstream and downstream stages of the innovation process in isolation, with a predominant focus on the former, that is, technological invention. Turning invention into innovation also requires capabilities such as design and marketing (Mendonça 2014; Rodríguez-Pose and Lee 2020), which are critical for developing a persuasive innovation that is more likely to be adopted. Hence, focusing on technology alone can result in a misrepresentation of the innovation process, leading to a bias in the preferred policy options, too (Breznitz 2021). Regional innovation systems can combine capabilities in all the complementary activities needed for innovation, but they also often specialize in specific ones, and not all regions can or wish to be technology leaders (Asheim and Coenen 2005; Capello and Lenzi 2013).

Recognizing the different specializations open to regions is also at the core of policies toward smart specialization strategies (S3) (Foray and Hall 2011). The program aims at taking a broad view on innovation. Yet, regional policy makers and scholars alike struggle to capture the diversity of innovation specializations and end up focusing on one type of specialization at a time (Foray, Morgan, and Radosevic 2018). Most often the focus is on specialization in science and technology activities: this can be explained with the belief that investing in the upstream stages of innovation will naturally lead to all kinds of innovations being introduced in the market (Marques and Morgan 2018) but also with the fact that those innovation activities have been easier to monitor with data (Castaldi and Mendonça 2022). All this has left many regions, especially those that are not high-tech clusters, struggling with recognizing and valuing their specific innovation capabilities and their ability to build smart specializations from them (Radosevic 2018).

The objective of this article is to develop a conceptual framework to understand the emergence of regional innovation specializations spanning a broader set of innovation activities than those focused on technological invention only. Our aim is to offer a framework that resonates with insights from theorizing and empirical findings of prior research, while being applicable in quantitative analyses of regional specializations, for policy and research purposes alike.

For the theoretical embedding, we leverage and extend the principle of relatedness (Hidalgo et al. 2018) and insights from evolutionary economic geography on related diversification (Boschma 2017). To do so, a first conceptual step relies on clarifying the distinction between invention and innovation: we propose to separate three different activities, namely, technology, design, and market. For each activity, we discuss the key properties and conceptualize the underlying knowledge space and then discuss how relatedness can be defined in each space. A second conceptual step involves connecting the three innovation activities by introducing the idea of *cross-relatedness* and the possibility of capturing an overall innovation space. By space we refer to a network where one can represent which innovation activities tend to cospecialize at the regional level. The cospecialization is depicted as a connection, with the innovation activities being the nodes in the network. Patterns of relatedness (*within* each innovation activity) and cross-relatedness (*between* innovation activity) can then be used to model the emergence of new regional innovation specializations, of the three different kinds.

For the operationalization, we propose a comparable set of innovation metrics that have not been systematically combined in regional innovation studies before. We capture the three innovation activities by three types of intellectual property rights (IPRs): (1) (utility) patents, (2) industrial designs, and (3) trademarks. These data allow us to operationalize relatedness and cross-relatedness using the underlying patent, design, and trademark classifications. We apply our empirical model to two independent settings for the period 2003–16. The first is 259 NUTS-2 regions across 21 European countries: this setting is the most salient in relation to smart specialization policy applications. The second is 363 metropolitan statistical areas (MSAs) areas in the US, an alternative testbed where the different definition of industrial designs enables us to compare the role of two specific types of design activities, namely, technical and aesthetic ones.

We reveal three main patterns. First, relatedness plays a significant role in the emergence of new regional specializations for all three innovation activities, not only the upstream ones. Second, cross-relatedness of technology activities with downstream ones matters for the emergence of design and market specialization, in line with traditional technology-push models of innovation. Yet, cross-relatedness of design and market activities with technology also matters for the emergence of new specialization, albeit to a lesser extent than relatedness in the same innovation activity. Nonetheless these *backward linkages* are indicative of feedback loops and synergies between regional innovation activities. Finally, the comparison of the European and US contexts highlights the differential role of technical versus aesthetic design activities, while also informing the use of IPR metrics to capture such activities.

Regional Innovation and the Principle of Relatedness: Toward a Conceptual Framework

Unpacking Innovation: Technology, Design, and Market Activities

Innovation is more than invention: it requires turning a promising new idea into something that users are willing to buy or adopt. We conceptualize this process as made of three main activities: technology, design, and market.

New technology typically stems from dedicated research activities, which can be formal research and development (R&D) or informal on the job activities. The knowledge involved is often synthetic, typical of engineering sciences (Asheim and Coenen 2005). Engineers and other technology developers will consider options across a *technology space* (Dosi 2000). A rich empirical literature has used patent data to reconstruct how companies and/or regions navigate the underlying technology space by following clear trajectories of learning (e.g., Leten, Belderbos, and Van Looy 2007; Rigby 2015), showing a high degree of path dependence.

Eventually, the new technological options can lead to a new product or a new process, but these will have to be further developed and designed before they can actually be applied and used. Design activities include prototyping and tryouts. When presented with new technological options, designers will work by navigating alternative design options in what can be defined as a *design space* (Windrum, Frenken, and Green 2017). Design can be seen as an intermediary function, concerned with finding solutions to trade-offs between technical feasibility and users' preferences (D'Ippolito 2014). Such a role is highly specific to technology-driven innovation processes, where designers are typically called upon only once new technologies emerge. Instead, design can take a more leading role in innovation processes typical of industries where soft innovation is the main source of change (Stoneman 2010). There, designers focus on aesthetic design options and the creation of new meanings, often with the aim of initiating new product lines and allowing differentiation (Verganti 2006).

Working product or process configurations will find their way to the market in the commercialization stage. In this last stage of the innovation process, capabilities related to marketing appear crucial. The success of an innovation depends not only on the quality of the innovation but also on the extent to which it aligns with needs and aspirations of consumers. In this phase, symbolic knowledge related to the definition of new categories and meanings comes into play (Mendonça, Santos Pereira, and Godinho 2004). When positioning the innovation, firms will consider profiling their offering as a specific option in what can be called the market space. To illustrate the point, Davids and Frenken (2018) reconstruct how Unilever positioned margarine as a (healthy) food product after being first introduced as a medical product. Patterns of regional and corporate market diversification and specialization can be captured with trademarks (Castaldi and Mendonça 2022).

Table 1 summarizes the key features of the three innovation activities as the building blocks for our framework of regional innovation specialization. Based on the discussion

Table 1

Three Key Innovation Activities and Their Properties

Innovation Activity	Technology	Design	Market
Main output	Technological inventions	Novel designs	New products (goods and services)
Phase of the innovation process	Research	Design and prototyping	Product development and marketing
Type of knowledge	Technological, synthetic, engineering-based	a. Technical design, in technology-driven innovation b. Aesthetic design, in soft innovation	Symbolic knowledge, categories, meanings
Knowledge space	Technological space	Design space	Market space
Proxy/Metric	Patents	a. Design patents b. Designs	Trademarks

above, design activities can be of two kinds. A first kind concerns what one could call technical design: these activities are common in technology-driven innovation processes and often involve designers trained at engineering schools, able to combine design thinking with synthetic knowledge bases typical of technology activities. A second kind concerns aesthetic design: those activities are common in soft innovation processes where designers focus on the creation of new products and new meanings, hence combining design knowledge with symbolic knowledge. These designers are more likely to be trained in art schools or dedicated design schools. The last row also includes the metrics that we will use for each activity, which we will explain in detail in "Methods." Next, we move to explain how regional specializations can stem from all three activities.

Regional Innovation Specializations and the Principle of Relatedness

As already hinted in the previous subsection, innovation activities tend to develop in a path-dependent manner, and the opportunities for further diversification or specialization get shaped by the knowledge and capabilities already developed at each point in time (Boschma 2017). This intuition from evolutionary economics has been conceptualized into the *principle of relatedness* (Hidalgo et al. 2007) and extensively applied within evolutionary economic geography. When it comes to innovation activities, researchers have provided strong evidence for the significance of relatedness in shaping the emergence of new regional technological specializations (Kogler, Rigby, and Tucker 2013; Boschma, Balland, and Kogler 2015; Petralia, Balland, and Morrison 2017; Apa et al. 2018). The rationale is that regions will branch out into new technologies that are related to their existing technological capabilities by tapping into and recombining existing knowledge bases. The underlying mechanism behind related diversification relies on the idea that related pieces of knowledge and capabilities are easier to be recombined thanks to cognitive proximity (Rigby 2015). At the same time, knowledge spillovers are not the only mechanisms supporting relatedness. As Boschma (2017) discusses, regions can show specialization in the same two activities because of knowledge spillovers, skill relatedness, or input–output relations: hence, relatedness can stem both from similarity and complementarity.

Scholars have used the principle of relatedness to examine branching in several economic activities in addition to technological ones, including export products (e.g., Hidalgo et al. 2007), industries (e.g., Neffke, Henning, and Boschma 2011), and scientific fields (e.g., Boschma, Heimeriks, and Balland 2014). Key to our arguments in this article is that the underlying logic of new knowledge emerging from the recombination of related bits of existing knowledge appears indeed to apply to different kinds of knowledge not only technological one. To illustrate how the logic is helpful to conceptualize developments in all the three knowledge spaces of technology, design, and market, we refer to an example. Smart phone technologies recombine technologies related to batteries, chips, antennas, audio, video, display, and the internet (Castaldi, Frenken, and Los 2015). At the same time, one can view the corresponding product, that is, the smart phone, as defining a new product category that recombines communication devices, photographic instruments, fashion items, and recreational services (Suarez, Grodal, and Gotsopoulos 2015). Similarly, smart phone product developers have experimented with different design options, often working around trade-offs in the size, power, and portability of the new devices (Cecere, Corrocher, and Battaglia 2015).

What this example illustrates is how knowledge spillovers exist for all knowledge types. Within technology spaces, technological similarity or complementarity will tend to support cognitive proximity. Within design spaces, design options where regions tend to cospecialize can be seen as closer to each other because of similar or complementary types of design solutions. With product spaces, similar or complementary symbolic knowledge will make regional specializations in two given product categories more likely than in two categories without a common or connected meaning.

If the principle of relatedness can indeed apply to all three innovation activities, then we can derive hypotheses about the emergence of new regional specializations in design and market activities that are similar to those about technology specializations. Specifically, we expect regions to be more likely to develop new innovation specializations when they show a high degree of relatedness of knowledge in each specific space.

From Relatedness to Cross-relatedness between Innovation Activities

The discussion above has treated the three innovation activities as independent ones. Yet, there are many ways in which innovation activities are related, through formal input–output relations but also knowledge feedback loops and even skill relatedness. The three knowledge spaces are also likely to be strongly connected to each other, since opting for specific technologies often comes with restricted design and market choices, and the other way around. These linkages allow expanding the notion of relatedness to include cross-relatedness as well.

We are not the first to extend the principle of relatedness to more knowledge dimensions. Catalán, Navarrete, and Figueroa (2020) focus on how scientific capabilities of a nation can contribute to new related technology specializations and define a *sci-tech space*. Pugliese et al. (2019) leverages a complexity perspective to investigate multilayered networks of relations between science, technology, and product capabilities of countries. Our work differs in several respects. First, our interest is in the regional level. Research has demonstrated that both national and regional systems of innovation are important, but the regional level allows capturing variance in innovation activities that is left unexplained when taking a national lens (Cooke, Uranga, and Etxebarria 1997). Second, our focus goes beyond the scientific base of regions and concerns, instead, the more applied stages of innovation, those mostly happening within corporate borders. Pugliese et al. (2019) include downstream activities by considering new product specializations, using export data. Such data are not focused on innovation and also tend to underestimate service activities, which are harder to trade. Finally, both studies assume a linear relation from science to technology and then market. Instead, our framework can accommodate cross-relatedness to run both ways, from upstream to downstream but also the other way around.

Based on our characterization of the three innovation activities, we propose to conceptualize relatedness between activities, that is, cross-relatedness, as the co-occurrence of specialization in two different innovation activities as revealed by the patterns at the supraregional level (whole Europe or whole US, in our case).

Cross-relatedness and Regional Innovation Specializations

We discuss here the mechanisms behind cross-relatedness that we expect to play a role. Similar to the understanding of relatedness, the mechanisms may be quite diverse: while it is hard to discriminate them empirically (Boschma 2017), we can discuss those that are most likely to be at play. In the first place, co-occurrence of two focal innovation activities, say design and market ones, in one region can be there because local companies possess knowledge that is useful for both activities, hinting at synergies in the underlying learning processes (Farinha et al. 2019). In the second place, there might be more formal input–output relations that connect innovation activities from technology to market (Essletzbichler 2015).

Starting with the ideas of the linear model of technology-push innovation, one could expect clear patterns of cross-relatedness of technology to the downstream innovation activities. From a different perspective, Chan, Mihm, and Sosa (2017) show how technological advances can push the boundaries of designs and even alter the styles of entire product segments. In general, one would expect regions cospecializing in technology and technological design activities to rely on similar or complementary knowledge bases (Corradini and Karoglou 2022). Such *tech-design relatedness* would likely stem from underlying synergies in technology-driven innovation (Murmann and Frenken 2006; Dan, Spaid, and Noble 2018) and mostly concern technical design. In such processes, *tech-market relatedness* would also be there, as working combinations of synthetic and symbolic knowledge bases feed cospecialization in specific technologies and specific markets (Hise et al. 1989; Breznitz 2021).

On the other hand, demand-pull arguments might also be mechanisms for cross-relatedness between innovation activities. Firms may experience synergies from embedding technological advances into their branded products/services as a way to deal with increased competition (Greenhalgh and Rogers 2012). For instance, Bei (2019) shows how firms may source technology from other firms to capitalize on their already successful brands. There is also evidence that clusters of firms with strong market positions have incentives to invest in new technological specializations to keep their products up to speed with technological upgrades (Fritsch and Wyrwich 2021). This suggests synergies that would support *market-tech relatedness*, too.

As for cross-relatedness between design and market activities, mechanisms supporting regional cospecialization can also run both ways. They are likely to be strongest when aesthetic design is concerned, relying on synergies between design and symbolic knowledge. In fact, design knowledge specialization can be leading in creating synergies with specific market knowledge bases (Walsh 1996; D'Ippolito 2014), but there is also rich evidence of significant feedback loops that design activities rest upon, with market demand or user feedback shaping new product aesthetics and functionalities (Di Stefano, Gambardella, and Verona 2012). These mechanisms are likely to be more evident in the case of aesthetic design and for industries where soft innovation works as a key competitive advantage.

Let us also stress two main reasons *not* to expect cross-relatedness. A first reason might be that the three innovation activities are independent or to a large extent separable. Within global or even simply modularized value chains, inventions can occur in one place and commercialization in another. If this is the case, then our framework would pick up the resulting lack of cross-relatedness and demonstrate it for those specific types of activities for which indeed separation is possible. A second reason is that downstream innovation activities may not need technological inventions to capitalize from. In several low-tech sectors, innovation rests upon *soft* elements or gets prompted by user feedback: this is the case in many service sectors but also in the creative and cultural industries (Millot 2009; Schmoch and Gauch 2009; Stoneman 2010).

Relatedness, Cross-relatedness, and Regional Innovation Specializations

Our framework suggests that regional innovation specializations in each innovation stage can be explained by both relatedness in that activity and cross-relatedness with the other two activities. Table 2 illustrates this in a matrix form, where the diagonal elements are the relatedness elements expected to be positively associated with each regional innovation specialization (the three column headers). The goal is to elaborate on which relatedness and cross-relatedness dimensions we expect to play a more pronounced role for the different innovation specializations. We do so by considering the two types of design, which will also correspond to the two empirical contexts where we test our hypotheses.

For all three innovation specializations, we expect the relevant relatedness measure (i.e., the diagonal elements in Table 2) to reveal the strongest association with the emergence of new specialization, following prior theoretical and empirical literature.

For technological specialization, we also expect cross-relatedness with downstream activities to play a role but less than relatedness. We expect tech-design relatedness to be positively associated with new technological specialization mostly when design is of a technical nature. Here the underlying synergies between technological and design knowledge appear more evident.

For design specializations, we expect differences for technical design versus aesthetic design, with a stronger role for tech-design relatedness, leveraging clear synergies between synthetic and design knowledge bases versus a stronger role for design-

Table 2

Relatedness and Cross-relatedness behind Regional Innovation Specializations: Expected Strength of Relationships Depending on Type of Design Activity

	Regional Innovation Specializations		
Dimensions of (Cross-)relatedness	**Technology Specialization**	**Technical Design Specialization**	**Market Specialization**
Technology	Technological relatedness (+++)	Tech-design relatedness (++)	Tech-market relatedness (++)
Technical design	Design-tech relatedness (+)	Design relatedness (+++)	Design-market relatedness (+)
Market	Market-tech relatedness (+)	Market-design relatedness (+)	Market relatedness (+++)
Dimensions of (Cross-)relatedness	**Technology Specialization**	**Aesthetic Design Specialization**	**Market Specialization**
Technology	Technological relatedness (+++)	Tech-design relatedness (+)	Tech-market relatedness (++)
Aesthetic design	Design-tech relatedness (+)	Design relatedness (+++)	Design-market relatedness (++)
Market	Market-tech relatedness (+)	Market-design relatedness (+)	Market relatedness (+++)

Note: the +++ signs summarize the hypothesized relationship and its strength, with +++ denoting the strongest association in that column, + the weakest, and ++ the intermediate one.

market relatedness, leveraging clear synergies between design and symbolic knowledge bases.

For market specializations, we similarly expect market relatedness to reveal the strongest association, but cross-relatedness with more upstream activities should also significantly matter. We envision a role for design-market relatedness, in case of aesthetic design, and for tech-market relatedness overall.

Intellectual Property Rights as Innovation Proxies

To capture technological inventions, design, and market activities, we consider utility patents, industrial designs, and trademarks. The main advantage of opting for these three metrics is that they are all intellectual property rights, with comparable types of data, and some common strengths and limitations. Key common strengths are that IPRs can be counted at the regional and national level, and they are registered after undergoing a formal filing procedure where specific requirements are checked. Key common limitations are at least two. First, their validity as innovation metrics is weakened by strategic practices in their filings (Greenhalgh and Rogers 2010). One way to take into account this problem is to consider only filings that made it to registration, which allows disregarding at least some of the strategic practices. This is the approach we opt for in our analysis. Second, IPRs only measure a share of all activities that contribute to innovation. However, they do capture activities that add value to the economy. At the regional level, there are several studies that relate at least one of these IPRs, and sometimes more than one, to innovation and/or entrepreneurship (Mendonça 2014; Torres-Preciado et al. 2014; Corradini and Karoglou 2022; Drivas 2022; Pinate et al. 2022) while Filippetti et al. (2019) show that regions engaging in all three types of IPR activity appear more economically resilient.

Utility patents have been employed most extensively as an innovation metric to capture technological inventions and the upstream phase of innovation processes (Griliches 1990). While researchers have critiqued the patent system, since several inventions may not pass the patentability threshold (Bessen and Meurer 2008; Boldrin and Levine 2013), scholars have also shown that patents can provide financial incentives to inventors; hence, they are specifically used by actors more strongly investing in invention (Moser 2005; Lerner 2009).

Design rights protect the aesthetics of industrial products and have been discussed as potential metrics for innovation (Stoneman 2010; Filitz, Henkel, and Tether 2015; Filippetti and D'Ippolito 2017; Heikkilä and Peltoniemi, 2019). Through the use of design rights, researchers have shown the evolution of products and styles in an entire industry (Chan, Mihm, and Sosa 2017). All prior studies have focused either on the US or Europe, but a key difference between the two systems is that in the US they are actually design patents, while in Europe design rights are more similar to trademarks (Schickl 2013). As such, in the US, design rights undergo a similar procedure to patents and are tested for novelty and industrial applicability, while design rights in Europe capture new designs that fulfill the condition of distinctiveness. This institutional difference allows connecting US design patents primarily to new technical designs and technology-based innovation processes and European design rights primarily to new aesthetic designs typical of industries focused on soft innovation. Hence, it also allows testing for hypotheses involving technical design in the US context and those involving aesthetic design in the European context.

Trademarks are distinctive signs that protect differentiating attributes of a product or service (Graham et al. 2013). Empirical studies have found significant evidence that trademarks correlate positively to innovation activity and new product/service introduction (Mendonça, Santos Pereira, and Godinho 2004; Flikkema, de Man, and Castaldi 2014; Flikkema et al. 2019). What distinguishes trademarks from the other IPRs is that the applicant needs to provide evidence of use in commerce before being granted (Graham et al. 2013; Schautschick and Greenhalgh 2016). Hence, trademarks can capture the most downstream stage of innovation activity.

Utility patents can be classified according to the International Patent Classification (IPC). Design rights are classified by the international Locarno classification of design categories: these categories concern industrial design and connect to specific artifacts. Therefore, these Locarno categories have an intuitive connection with both patent classes, since patents have to indicate an industrial application, and trademark classes, since they indicate specific product categories that identify the specific markets where trademark owners claim protection. Trademark classes are defined by the international Nice classification, including forty-five classes (one to thirty-four cover goods, and thirty-five to forty-five cover services). A strength of combining these classifications is that the three are internationally comparable. A limitation is that they differ in the degree of detail, with patent classes being the most detailed, followed by design and trademark classes.

Methods

Data Collection

Starting with Europe, we collected utility patents filed at the European Patent Office (EPO) from the OECD's REGPAT database (Maraut et al. 2008), including applicant's NUTS-2 information, and trademark and industrial designs filed at the European Union Intellectual Property Office (EUIPO). Each EUIPO record was separately located in an XML file, and after a careful reconfiguration, we obtained each applicant's country and postal code information. We assigned each postal code to a NUTS-2 region based on the European Commission's NUTS-2 postal codes concordance.[1] We included a country's NUTS-2 regions if more than 90 percent of the country's trademarks and industrial designs were assigned to a NUTS-2 region. The countries that did not satisfy this criterion were Bulgaria, Ireland, Romania, and Lithuania.[2] Further, we dropped countries that only included a single NUTS-2 region as in Xiao, Boschma, and Andersson (2018): Estonia, Cyprus, Luxembourg, Latvia, and Malta. Finally, we included Switzerland and Norway though they are not part of the EU, due to the proximity to other EU countries. Overall, we obtained information for approximately 450,000 patents, 640,000 industrial designs, and 570,000 trademarks, filed during 2003–16, which made it to registration and were spread over 259 NUTS-2 regions.

For the US case, we collected utility patent, design patent, and trademark records from the public databases of the United States Patent and Trademark Office (USPTO).[3] In line with other studies, we chose the MSA level as the geographic level most comparable to NUTS-2 regions (Lee and Rodríguez-Pose 2013).[4] For each USPTO record, we obtained the application and registration dates, the associated classes, and the location information of the applicant. Note that patents can also be counted by inventor location, but since trademarks can only be counted by owner location, we opt for the applicant location for all IPRs. For both utility and design patents, the USPTO has already geocoded the applicants; hence, we only needed to assign the coordinates to MSAs based on the US census's Topologically Integrated Geographic Encoding and Referencing shapefiles, 2010 version. For the case of trademarks, we used the postal codes and assigned them to MSAs based on the same shapefiles. Missing postal codes were searched in Google Earth Pro and, based on their coordinates, were once again assigned to an MSA. Overall, we obtained information for approximately 1 million utility patents, 137,000 design patents, and 3.6 million trademarks, filed during the period 2003–16, which made it to registration and which were assigned to 363 MSAs.

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1 https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts.

2 For Bulgaria, Ireland, and Romania, we could not locate the postal code for approximately 50 percent of the trademark filings from the database. For Lithuania, while we could locate a postal code for the trademark application data, we could only obtain a three-digit postal code. However, from the European Commission's NUTS-2 postal codes concordance, we could only locate a five-digit postal code, thereby excluding this country due to the lack of clear concordance.

3 Office of the Chief Economist, https://www.uspto.gov/ip-policy/economic-research/research-datasets. For a thorough overview of this trademark database, see Graham et al. (2013).

4 Lee and Rodríguez-Pose (2013) focused on MSAs and NUTS-1 regions when comparing US and European regions. However, wherever data availability allowed them to use NUT-2 regions, they performed the analysis at that level.

For utility patents, the standard practice in the evolutionary economic geography literature is to focus on either the three-digit (Balland et al. 2019) or four-digit IPC classification (Apa et al. 2018). Given the higher level of detail, we opt for the first listed four-digit IPC classification. For design rights, we employ the four-digit classification Locarno classification. For trademark classes, we rely on the forty-five Nice classes, but we discuss possible extensions in the robustness tests and conclusions.

Finally, we decided to count IPRs by filing year, that is, the year closest to the underlying activity taking place, but we only counted registered IPRs. This allows counting IPR filings that underwent the administrative checks of the formal requirements and hence are likely to be of higher quality than filings that did not make it to registration. This choice also explains why our sample ends in 2016. Because of the known lags between filing and registration, we can exploit more recent information to check registration. Note that EUIPO only started accepting industrial design applications in 2003; therefore, to provide an even comparison across both testbeds, our samples start in 2003.

Key Variables

Our approach relies on calculating relatedness measures for all three innovation metrics. In doing so, we first build technology, design, and market spaces, and then a comprehensive innovation space, where the three activities are related to each other. For patents and design rights, we consider the main primary listed class. For the case of trademarks, we opt for whole counting, in case there is more than one Nice class disclosed. Unlike patents, and design rights, for an applicant to claim an additional class s/he needs to provide evidence that the trademark is used in commerce in all selected classes of goods/services. Therefore, a trademark with several classes has a wider scope of commercial activity compared to a trademark with a single class. Nonetheless, we run several robustness checks where we opt for alternative choices of the listed classes.

We discuss here the construction of the innovation spaces for the European case and provide examples specific to this context. The analysis for the US follows exactly the same steps. First, we bundle years in three time periods: 2003–08, 2009–12, and 2013–16. Therefore, the period dimension, denoted as t, takes three values: $t=0$ for 2003–8, $t=1$ for 2009–12, and $t=2$ for 2013–16. Working with periods instead of single years ensures that a region's entry into a new specialization is robust and not due to a random short-term shock (Neffke, Henning, and Boschma 2011). We first constructed the indicator of specialization that has become standard in the relatedness literature, inspired by Balassa (1965). The indicator identifies whether region r has a revealed comparative advantage (RCA) in class i for a particular IPR during period t. For instance, for market specializations, the RCA is defined as

$$RCA_{r,i,t} = \frac{trademarks_{r,i,t} / \sum_i trademarks_{r,i,t}}{\sum_r trademarks_{r,i,t} / \sum_r \sum_i trademarks_{r,i,t}}$$

In other words, $RCA_{r,i,t}$ at period t measures the share of trademarks in class i that region r filed over the share of trademarks filed in class i of all trademarks filed. Therefore, a higher $RCA_{r,i,t}$ implies that region r is relatively more active in trademark class i

compared to the entire set of regions. Similar specialization indicators are calculated for patents and design rights. To have a class index that runs through all three classifications, we recode class i to be a numeric index that takes values between 1 and 836 (1 and 822) for Europe (US). This comes from the fact that for Europe (US), we have 589 (591) 4-digit IPC classes and 202 (186) Locarno classes, and 45 Nice classes.

Following the literature (Hidalgo et al. 2007), a region is specialized in class i if its RCA is above one:

$$x_{r,i,t} = \begin{cases} 1 \; if \; RCA_{r,i,t} > 1 \\ 0 \quad otherwise \end{cases}$$

The next step generates the key inputs for constructing the innovation spaces capturing the underlying relatedness and cross-relatedness. Following the literature, we start by estimating proximities among classes from revealed patterns of cospecialization. We calculate the probability that a region specializes in class i, given that it also specializes in class j. For the 259 NUTS-2 regions (or 363 MSAs) we count the instances where class i has an RCA > 1 given that class j, where $i \neq j$, has an RCA > 1. Then by dividing this number with the instances where class j has an RCA > 1, we obtain the probability $P(x_{i,t}|x_{j,t})$. This probability does not need to be equal to the opposite conditional probability $P(x_{j,t}|x_{i,t})$. To reconcile this asymmetric distance between classes, we follow Hausmann and Klinger (2007) and calculate the minimum of each pair of probabilities. That is

$$\varphi_{i,j} = \min \{P(x_{i,t}|x_{j,t}), P(x_{j,t}|x_{i,t})\}$$

For the European (US) case, $\varphi_{i,j}$ populates an 836×836 (822×822) matrix of proximities that capture the overall innovation space. Note that this matrix is symmetric by definition, as $\varphi_{i,j} = \varphi_{j,i}$ for each given combination of i and j.

Figures A1 and A2 in the online material display the innovation space for Europe and the US, respectively. After summing all φ's, we calculate the minimum spanning tree (MST) algorithm to display the edges between nodes. For both geographic contexts, we observe several clusters where technology, design, and market activities are interconnected. For the case of Europe, trademark market classes are linked with many technology classes within a core cluster comprised of loosely connected smaller clusters. In the case of the US, the picture is slightly different with trademark market classes dispersed across the innovation space instead of within a central cluster. Let us provide some examples that illustrate how the specific patterns of relatedness and cross-relatedness have mattered for shaping new regional specializations. In Europe, specializations in industrial designs on locking and closing devices tend to co-occur with designs in chain links and permanent magnets but also with patents on bolts, hinges, and devices for opening and closing any type of wing. The DE11 region (Stuttgart) displayed a new specialization in locking and closing devices after it had developed specializations in both the related design and patent fields. In the US, the MSA of Tampa-St. Petersburg-Clearwater, FL, exhibited a new market specialization in clothes and footwear trademarks after it already specialized in patents that include inventions in outerwear, protective garments, and accessories.

Going beyond these specific examples, our analysis aims at establishing to what extent regional relatedness and cross-relatedness matter on average for the emergence of new regional technology, design, and market specializations. To this end, we estimate regression models that allow us to gauge the strength and directionality of relatedness within and between the three innovation activities on the emergence of new regional specializations. The dependent variables capture the entry of region *r* in a new specialization in a particular class *i*. They take the value of 1 if region *r* exhibits an RCA in period *t*, given it had not in period *t-1* and 0 otherwise. That is

$$Entry_{r,i,t} = \begin{cases} 1 \ if \ x_{r,i,t} = 1 \ \ and \ x_{r,i,t-1} = 0 \\ 0 \qquad otherwise \end{cases}$$

We then construct the main independent variables of interest, capturing regional relatedness within and between types of IPRs. Following the literature, we use average density measures, as they are called in the literature, which consider proximities of the focal class to the classes where the region already specializes. For exposition, assume that our interest is on $Entry_{r,i,t}$ where $i = 1\text{-}45$, that is, we focus on new market specializations. We construct three variables. The first one captures relatedness specific to market activities:

$$Market\_RELATEDNESS_{i,r} = \frac{\sum_{j=1, j \in r, j \neq i}^{45} \varphi_{ij}}{\sum_{j=1, j \neq i}^{45} \varphi_{ij}}$$

The numerator is the sum of φ_{ij} in the trademark class *j* in which region *r* specializes. The denominator is the overall sum of φ_{ij} for market class *i*. This measure captures how embedded trademark market class *i* is in the rest of the regional market activities.

The other two variables, capturing cross-relatedness, are

$$TechMarket\_RELATEDNESS_{i,r} = \frac{\sum_{j=46, j \in r, j \neq i}^{634} \varphi_{ij}}{\sum_{j=46, j \neq i}^{634} \varphi_{ij}}$$

$$DesignMarket\_RELATEDNESS_{i,r} = \frac{\sum_{j=635, j \in r, j \neq i}^{836} \varphi_{ij}}{\sum_{j=635, j \neq i}^{836} \varphi_{ij}}$$

These two variables capture the relatedness of class *i* to technology and design classes where the region also specializes.

Similar variables are constructed for the models, explaining the emergence of new technological and design specializations. Note that cross-related density measures are not symmetric: *TechMarket* cross-related density is different from *MarketTech* related density, given that the variables depend on the regional specializations.

Econometric Specifications

To examine the role of the different relatedness measures for new specializations, we consider separate regressions for each innovation specialization. Each regression can be understood as the operationalization of the relations in the three columns of Table 2, which summarizes our conceptual framework.

For new market specializations we consider

$$\begin{aligned} &Entry_{r,i,t} = \alpha_0 + \alpha_1 Market\_RELATEDNESS_{r,i,t-1} + \\ &\alpha_2 TechMarket\_RELATEDNESS_{r,i,t-1} + \\ &\alpha_3 DesignMarket\_RELATEDNESS_{r,i,t-1} + \\ &RegionPeriod_{r,t} + ClassPeriod_{i,t} + \varepsilon_{r,i,t} \end{aligned} \tag{1}$$

For new technology specializations

$$\begin{aligned} &Entry_{r,i,t} = \beta_0 + \beta_1 Tech\_RELATEDNESS_{r,i,t-1} + \\ &\beta_2 MarketTech\_RELATEDNESS_{r,i,t-1} + \\ &\beta_3 DesignTech\_RELATEDNESS_{r,i,t-1} + \\ &RegionPeriod_{r,t} + ClassPeriod_{i,t} + \varepsilon_{r,i,t} \end{aligned} \tag{2}$$

For new design specializations

$$\begin{aligned} &Entry_{r,i,t} = \gamma_0 + \gamma_1 Design\_RELATEDNESS_{r,i,t-1} + \\ &\gamma_2 MarketDesign\_RELATEDNESS_{r,i,t-1} + \\ &\gamma_3 TechDesign\_RELATEDNESS_{r,i,t-1} + \\ &RegionPeriod_{r,t} + ClassPeriod_{i,t} + \varepsilon_{r,i,t} \end{aligned} \tag{3}$$

Note that the first period's (2003–8) information is utilized as lagged information for the period 2009–12. To this end, we can only observe entries in periods 2009–12 and 2013–16. Overall, we expect relatedness to be positively related to new specializations and hence $\alpha_1 > 0$, $\beta_1 > 0$ and $\gamma_1 > 0$. In addition, we expect cross relatedness measures to be positively associated with new specializations, too (i.e., $\alpha_2 > 0$, $\beta_2 > 0$, $\gamma_2 > 0$, $\alpha_3 > 0$, $\beta_3 > 0$ and $\gamma_3 > 0$). To be able to compare coefficients across regressions as well as interpreting them, all relatedness measures are standardized as in Xiao, Boschma, and Andersson (2018). Note that we only include region-class–period observations where the region did not display an RCA above 1 in period *t-1* (i.e., $x_{r,i,t-1} = 0$). If the region had already specialized in that class, then that region-class pair would add no information on the relation between the relatedness measures and new specializations. To take into account region and class intertemporal heterogeneity, we include both *region-period* and *class-period* fixed effects in all regressions. Due to the large amount of fixed effects, all regressions are estimated via ordinary least squares (OLS), since nonlinear estimators, such as probit and logit, are likely to produce biased estimates (Greene 2012; Boschma, Minondo, and Navarro 2013; Gomila 2021). Standard errors are clustered at the region-class level to avoid serial correlation (Bertrand, Duflo, and Mullainathan 2004).

Empirical Analysis

Descriptive and Graphical Analysis

Table A1 in the online material shows summary statistics of the dependent variables. For the European (US) case, there is a 13 percent (15 percent) probability that a new specialization will take place in a region-trademark class, while for patents and designs, the probabilities are 6 percent (5 percent) and 7 percent (5 percent), respectively. The lower likelihood of technology and design specializations is to be expected, given the larger number of technology and design classes as compared to the market classes. Also, we observe that the likelihood of new specializations is similar in the two geographic contexts. Tables A2–A4 show the correlations of the dependent and independent variables for Europe (Panel A) and the US (Panel B). Relatedness measures correlate strongly, which might result in a multicollinearity bias in the econometric analysis. To examine whether multicollinearity confounds the overall empirical results, we always include relatedness and cross-relatedness variables stepwise in the regressions.

Figures 1A–1C display the average relatedness measures for the period 2003–8 for European regions. Both average *Market_RELATEDNESS* and *Design_RELATEDNESS* are not always high (low) in regions with high (low) average relatedness in technological activities. The difference between market and design relatedness, on the one hand, and technology relatedness, on the other hand, suggests that the first two follow their own dynamics, which might be (at least partly) independent of technological ones. This also corroborates our intuition that EUIPO's designs relate to aesthetic design activities closer to market activities than technological ones. Figures 2A–2C display the average *Market_RELATEDNESS*, *Tech_RELATEDNESS*, and *Design_RELATEDNESS* for US MSAs. Similar to the European case, the map of market relatedness reveals a somewhat different pattern than technological relatedness. However, unlike the European case, regions tend to score similarly in terms of technology and design relatedness, and high scores often coincide with regions with strong technological profiles. This seems in line with the fact that USPTO design rights capture technical design activities.

Regression Results

In what follows, we present the baseline results for the market, design, and technology specializations, that is, Equations (1)–(3) referring to the three columns of Table 2. In the three tables, we include the results for Europe and the US. Starting with the more downstream innovation activity, we analyze the emergence of new market specializations in products and services (Table 3). Note that the variance inflation factor (VIF) for the case of Europe when all coefficients are included (Column 3) *Market_RELATEDNESS*, *TechMarket_RELATEDNESS*, and *DesignMarket_RELATEDNESS* are 1.18, 2.15, and

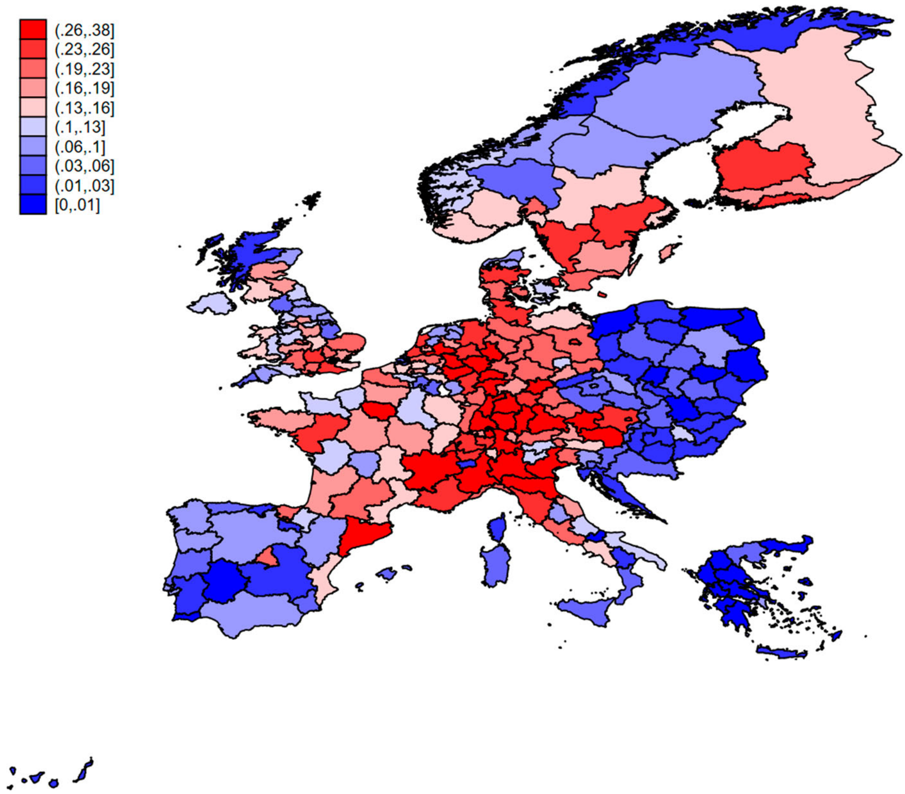

Figure 1A. Technology relatedness for the period 2003–8.

2.09 while for the US (column 6) the VIF tests are 1.12, 3.6, and 3.47. While these measures could be considered high, they are far from the critical threshold of 10 (Hair et al. 2006). Also, the stepwise inclusion of the relatedness measures (columns 1–3 and 4–6) does not reveal any dramatic change in the coefficients; hence, multicollinearity does not appear to be an issue.

For both geographic contexts, relatedness is significantly associated with new market specializations. As the independent variables are standardized, the coefficient in the full model for Europe (column 3) can be interpreted as follows: a one standard deviation increase of $Market\_RELATEDNESS_{r,i,t-1}$ from its mean is associated with an increase in the likelihood that region r will exhibit a new specialization in market class i of 22.0 percentage units. $TechMarket\_RELATEDNESS_{r,i,t-1}$ is also strongly associated with new market specializations. A result that stands out is that *DesignMarket_RELATEDNESS* is neither positive nor significant for the US case. We go back to this finding after presenting all baseline results.

Table 4 reports estimates for the role of relatedness in the emergence of new technological specializations. The VIF for *Tech_RELATEDNESS*, *MarketTech_RELATEDNESS*, and *DesignTech_RELATEDNESS* are 2.39, 1.24, and 2.32 for Europe (column 3), while for the US (column 6), they are 4.18, 1.14, and 4.11, respectively. Also in this case, multicollinearity is not an issue. *Tech_RELATEDNESS* is strongly associated with new technological specializations, in both contexts. Cross-relatedness measures are significant, but the

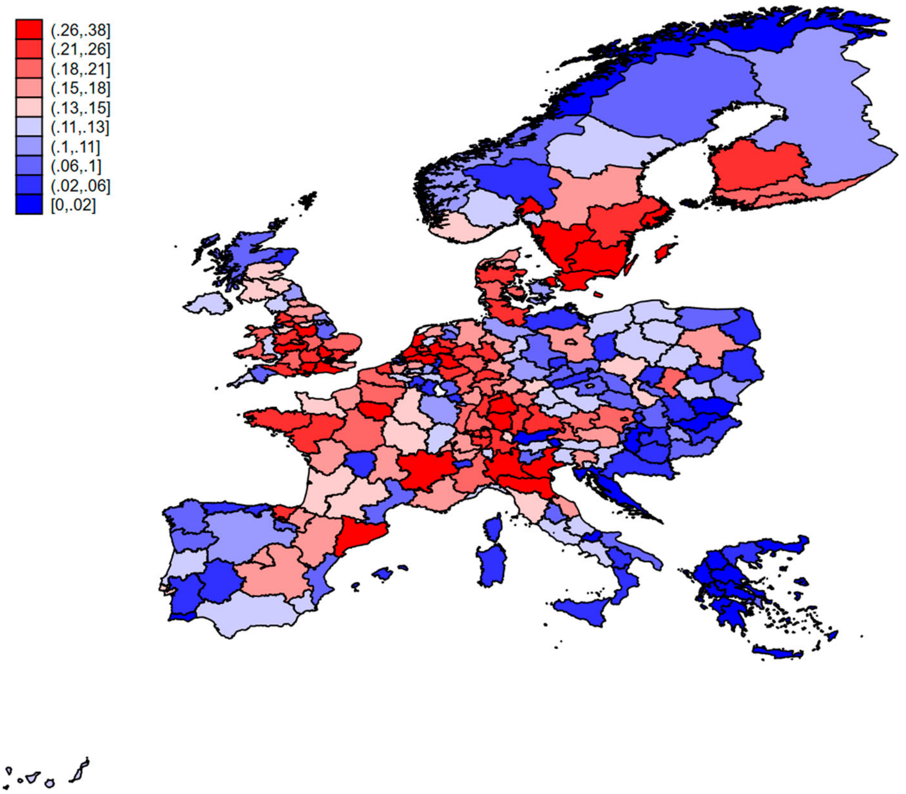

Figure 1B. Design relatedness for the period 2003–8.

coefficients are significantly lower than the *Tech_RELATEDNESS* coefficient (*t*-tests comparisons are statistically significant at $p < 0.01$), indicating that relatedness matters more than cross-relatedness when it comes to new technology specializations.

Table 5 displays estimates for the role of relatedness in new design specializations. The VIF for *Design_RELATEDNESS*, *MarketDesign_RELATEDNESS*, and *TechDesign_RELATEDNESS* is 2.29, 1.22, and 2.35 for Europe (column 3), while for the US (column 6), it is 4.03, 1.13, and 4.10, respectively. Once again, the stepwise inclusion of the variables does not reveal any multicollinearity issues. All relatedness measures are significantly and positively related to the emergence of new design specializations. For the US, cross-relatedness matters even more than relatedness, particularly when it comes to technology (*t*-test comparisons statistically significant at $p < 0.01$).

We can now relate our findings back to the framework and hypotheses we proposed in Table 2. We refer to the baseline results in Tables 3, 4, and 5, as the empirical counterparts of the three columns in Table 2, with the US context offering a testbed for the case of technical design and Europe for aesthetic design. We found that relatedness mattered the most in all regressions, in line with our expectations. There were two exceptions. For US regions tech-design cross-relatedness was as strongly associated with new design specializations as design relatedness, pointing to technical design specializations being strongly driven by technology. Also, for European regions, new market specializations were equally strongly associated with all relatedness and cross-

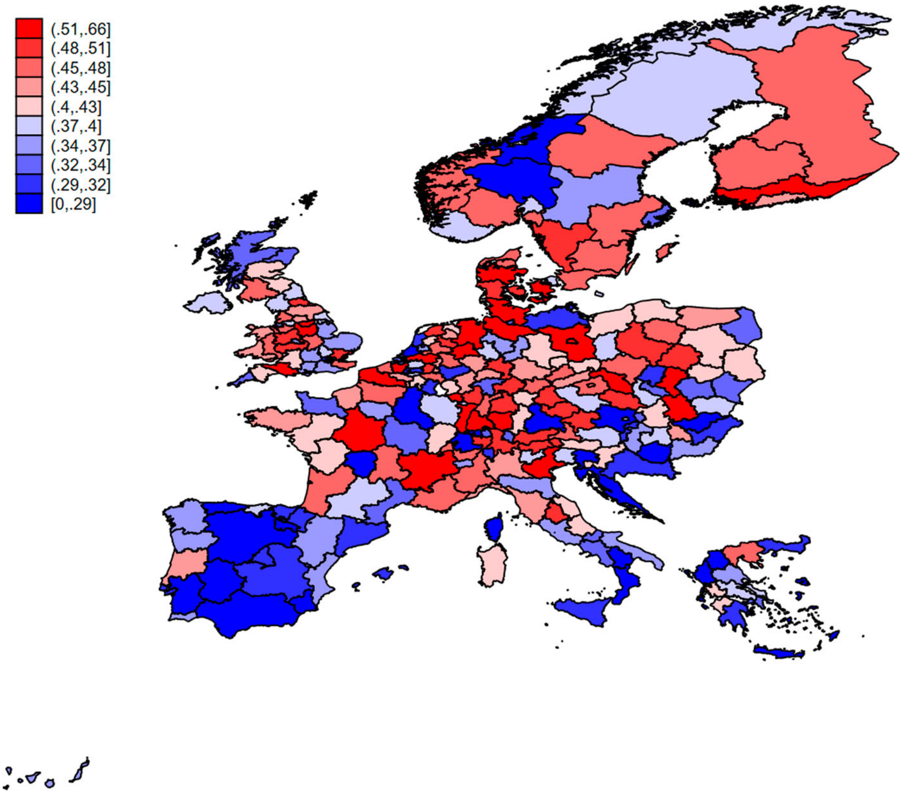

Figure 1C. Market relatedness for the period 2003–8.

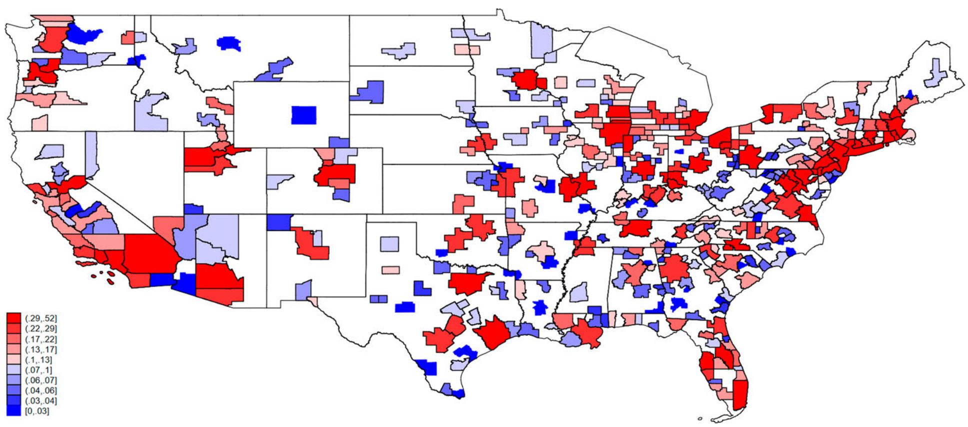

Figure 2A. Technology relatedness for the period 2003–8.

relatedness measures, suggesting strong synergies between all three innovation activities supporting market leadership.

A consistent pattern across both geographic contexts was that cross-relatedness with technology mattered when considering new market and design specializations, to an

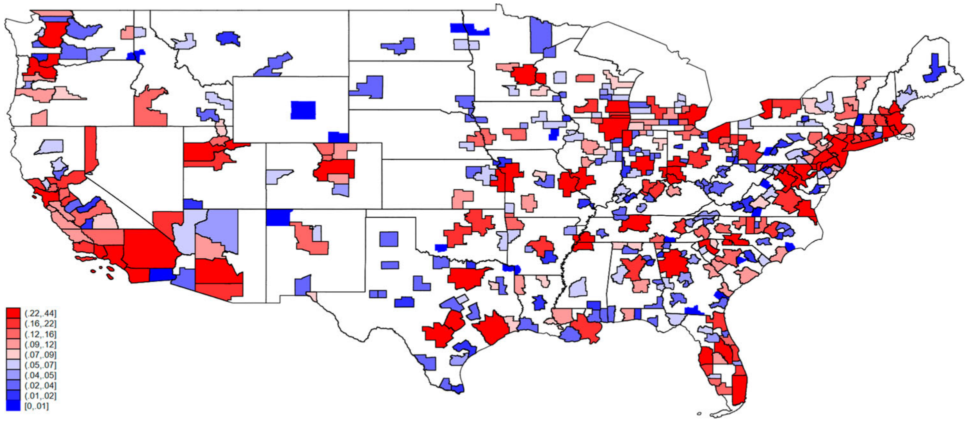

Figure 2B. Design relatedness for the period 2003–8.

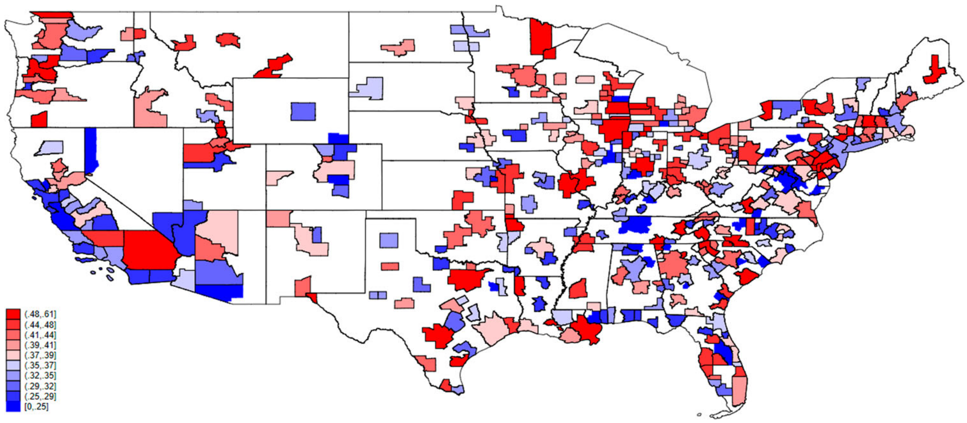

Figure 2C. Market relatedness for the period 2003–8.

extent comparable to relatedness and in line with the relevance of synergies from upstream to downstream activities. When focusing on new technology specializations, cross-relatedness with market and design mattered but much less so than technology relatedness, as expected for backward linkages from downstream to upstream.

Going back to the results for market specializations (Table 3), we noted that *DesignMarket_RELATEDNESS* played no role in the case of the US, while it exhibited a strong positive coefficient in the case of Europe. To further compare this finding to our intuition that indeed *DesignMarket* relatedness would mostly be there in technology-driven innovation processes, we also checked whether results changed when focusing on high-tech market specializations only. We focused on a subset of trademark classes that can be related to high-technology products, as suggested by Mendonça and Fontana (2011),[5] and then estimate the same regressions. Column 2 of Table 6 shows that for high-tech product market specializations, the coefficient of

[5] These high-technology product Nice classes are 1, 3, 5, 7, and 9–15.

Table 3

Role of Relatedness and Cross-relatedness for New Market Specializations

	Europe			US		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$Market\_RELATEDNESS_{r,i,t-1}$	0.228***	0.229***	0.220***	0.242***	0.248***	0.242***
	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.015)
$TechMarket\_RELATEDNESS_{r,i,t-1}$	0.158***		0.134***	0.137***		0.141***
	(0.041)		(0.041)	(0.043)		(0.044)
$DesignMarket\_RELATEDNESS_{r,i,t-1}$		0.171***	0.150***		0.002	-0.021
		(0.041)	(0.041)		(0.042)	(0.043)
Constant	-0.126*	-0.176***	0.014	-0.036	0.136**	-0.026
	(0.071)	(0.068)	(0.071)	(0.065)	(0.060)	(0.068)
Observations	14,336	14,336	14,336	21,011	21,011	21,011
R-squared	0.129	0.129	0.130	0.090	0.089	0.090
adj *R*-squared	0.090	0.091	0.091	0.053	0.053	0.053

Note: The dependent variable in all regressions is $Entry_{r,i,t}$. All regressions are estimated via OLS and include region-period and Nice class-period dummies. Columns (1)–(3) consider the European case while columns (4)–(6) consider the US case. Standard errors are clustered at the region-class level and are displayed in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 4

Role of Relatedness and Cross-relatedness for New Technology Specializations

	Europe			US		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$Tech\_RELATEDNESS_{r,i,t-1}$	0.194***	0.191***	0.188***	0.187***	0.181***	0.181***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$MarketTech\_RELATEDNESS_{r,i,t-1}$	0.011***		0.011***	0.005***		0.005***
	(0.001)		(0.001)	(0.001)		(0.001)
$DesignTech\_RELATEDNESS_{r,i,t-1}$		0.020***	0.019***		0.011***	0.012***
		(0.003)	(0.003)		(0.003)	(0.003)
Constant	-0.068***	0.046***	0.046***	-0.051***	-0.061***	-0.058***
	(0.010)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)
Observations	268,815	268,815	268,815	379,247	379,247	379,247
R-squared	0.089	0.089	0.089	0.115	0.115	0.115
adj *R*-squared	0.083	0.083	0.083	0.110	0.110	0.110

Note: The dependent variable in all regressions is $Entry_{r,i,t}$. All regressions are estimated via OLS. All columns include region-period and IPC class-period dummies. Columns (1)–(3) consider the European case while columns (4)–(6) consider the US case. Standard errors are clustered at the region-class level and are displayed in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 5

Relatedness and Cross-relatedness for New Design Specializations

	Europe			US		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$Design\_RELATEDNESS_{r,i,t-1}$	0.094***	0.086***	0.084***	0.088***	0.056***	0.056***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
$MarketDesign\_RELATEDNESS_{r,i,t-1}$	0.017***		0.015***	0.008***		0.006***
	(0.002)		(0.002)	(0.002)		(0.002)
$TechDesign\_RELATEDNESS_{r,i,t-1}$		0.053***	0.049***		0.099***	0.098***
		(0.006)	(0.006)		(0.005)	(0.005)
Constant	0.085***	0.077***	0.005	0.052**	0.062***	0.065***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.018)	(0.018)
Observations	91,686	91,686	91,686	123,493	123,493	123,493
R-squared	0.081	0.081	0.082	0.110	0.114	0.114
adj R-squared	0.072	0.072	0.073	0.102	0.106	0.106

Note: The dependent variable in all regressions is $Entry_{r,i,t}$. All regressions are estimated via OLS. All columns include region-period and Locarno class-period dummies. Columns (1)–(3) consider the European case while columns (4)–(6) consider the US case. Standard errors are clustered at the region-class level and are displayed in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 6

The Case of High-tech Product Market Specializations

VARIABLES	Europe (1)	US (2)
$Market\_RELATEDNESS_{r,i,t-1}$	0.225***	0.185***
	(0.030)	(0.034)
$TechMarket\_RELATEDNESS_{r,i,t-1}$	0.606***	0.289***
	(0.145)	(0.108)
$DesignMarket\_RELATEDNESS_{r,i,t-1}$	0.188*	0.174*
	(0.109)	(0.097)
Constant	-0.042	-0.118
	(0.167)	(0.099)
Observations	3,608	5,145
R-squared	0.221	0.181
adj R-squared	0.084	0.041

Note: The dependent variable in all regressions is $Entry_{r,i,t}$. Both columns consider Nice classes that are related to medium- and high-technology industries according to Mendonça and Fontana (2011). These Nice classes are 1, 3, 5, 7, and 9–15. All regressions are estimated via OLS. All columns include regionperiod dummies and Nice class-period dummies. Standard errors are clustered at the region-class level and are displayed in parentheses.

DesignMarket_RELATEDNESS for the US is indeed positive and significant. For consistency with the baseline, we also run a similar estimation for the European case (column 1). Overall, the results confirm the positive coefficients for all relatedness and cross-relatedness measures, suggesting strong synergies between all innovation activities for market specializations in high-tech products.

Robustness Checks

To provide robustness checks for the above results we consider several variations. Table A5 in the online material provides an overview of all the robustness results, to highlight similarities and spot instances where the results deviate from the baseline regressions. First, while we opted for OLS to include an array of fixed effects and control for unobserved heterogeneity, we wish to check that the choice of this estimator is not driving our results. To this end, we estimated all regressions via probit models, too. We had to drop class-period dummies due to convergence issues, but Table A6 in the online material reveals similar results to the baseline estimates. Note that the small change in sample size from the baseline results in the probit estimations comes from the fact that a few observations are predicted perfectly and hence are excluded.

Further, for the European case we had excluded five countries (Estonia, Cyprus, Lithuania, Latvia, and Malta) since they included a single NUTS-2 region. In Table A7 in the online material, we add these five countries as additional regions. Results are again similar to those of the baseline models.

We also validated several critical choices we made about our IPR metrics. A first issue is whether assigning patents to the inventor location, instead of the applicant location, makes a difference. Inventor location is available for USPTO and EPO patents and for USPTO design patents, while all trademarks and EUIPO design rights only include the applicant location. This is a well-known issue when combining patent and trademark data. There might be a headquarters effect, with regions hosting headquarters scoring higher on those activities measured with trademarks simply because trademark filings only include information on the applicant company. Yet it should be noted that activities related to marketing and commercialization tend to be more centralized at the headquarters level than upstream research activities anyways (Castaldi and Mendonça 2022). In Table A8 of the online material, we report results of the models after repeating all analyses with inventor locations for those IPRs where they are available. Results are comparable to the baseline ones.

Further, we estimated all regressions with variables calculated using all IPR filings, not only those that made it to registration. By doing so, we are including more filings, whose quality might be lower. Focusing on filings might be interesting for two reasons: first, it provides a timelier indicator, given that registration takes some time; second, it includes activities by companies that did not have the required financial resources or the expertise to obtain a successful registration. After reestimating the relatedness variables, Table A9 in the online material provides the counterparts of Tables 3, 5, and 6. Overall, results are quite similar.

We also validated our choices in terms of counting classes. On one hand, we considered fractional counting of trademarks instead of whole counting. After reconstructing all the variables, we perform the same analysis. Results are displayed in columns 1 and 4 of Tables A10–A12 in the online material for each new innovation specialization for the US and Europe.

On the other hand, a known limitation of trademark classes is that they are only forty-five, thereby potentially underestimating new trademark specializations, and also affecting any relatedness measure associated with the trademarks. While we cannot provide a direct robustness check with alternative versions of trademark classes, we can provide an indirect test. We considered technology classes (123 in total) at the three-digit IPC classification instead of the four-digit level, making the level of detail of patent classes more similar to trademark classes. In this case the $\varphi_{i,j}$ matrix for Europe (US) populates a 370×370 (354×354) matrix. If the aggregation for the forty-five Nice classes was problematic, then this analysis would deliver starkly different results, since the level of aggregation for IPC classes also changed dramatically. In columns 2 and 5 of Tables A10–A12 in the online material we reestimated the baseline models by whole counting trademarks, while in columns 3 and 6 we opted for fractional counting. In both cases we considered the three-digit IPC classification. The results are by and large similar to the baseline ones. Finally, we revisited the choice of considering only the first-listed IPC class.[6] We considered all the four-digit IPC classes for each utility patent, and Table A13 in the online material reports the alternative results. They are qualitatively similar with the exception of *DesignTech_RELATEDNESS*, whose coefficient for new technological specialization of US regions is not significant. Yet, the main result that relatedness has a stronger association than cross-relatedness remains.

[6] We did not pursue a similar robustness for design rights. Design patents in the USPTO data simply did not include any secondary Locarno class, while the EUIPO data only included it for 3.5 percent of the filings. Therefore, focusing on the first-listed Locarno class is the only option for the overwhelming majority of the data.

Conclusion

In this article we aimed to take seriously the calls from researchers and policy makers for a broader view on regional innovation specializations, beyond technology only. We developed a conceptual framework grounded on combining insights from innovation studies and evolutionary economic geography. In our framework we conceptualized three main types of innovation activities and argued that the principle of relatedness can be leveraged to understand branching to new specializations within and between the three innovation activities.

We also showed how IPR metrics can be used to capture developments in three underlying knowledge spaces of technology/patents, design/design rights, and markets/trademarks. Our empirical analysis of US and European regions in three recent periods provided support for an overall strong association of both relatedness and cross-relatedness measures with the emergence of new regional innovation specializations. This confirmed that path dependence and place dependence act as powerful forces in technological, design, and market trajectories. At the same time, we found that cross-relatedness played a significant role in the emergence of new regional specializations for all three innovation activities. Design appeared as an intermediary function lying in between the two other innovation activities and intertwined with both, albeit in different ways. The two geographic testbeds helped us to gauge the role of technical and aesthetic design activities. We found design-market cross-relatedness to matter for new market specializations in the European context, while that link was only there for high-tech product market specialization in the US case.

To expand further on policy implications, our results can inform the development and implementation of regional policies of smart specialization in several ways. First, considering more downstream specializations appears relevant, since actual innovation that has reached the commercialization phase is important to generate jobs and entrepreneurial opportunities in regions. In fact, the latest take on S3 smart specialization strategies (European Commission 2021, 2) acknowledges that “Social, organisational, market and service innovation, or practice-based innovation, play as important a role in S3 as technological innovation based on scientific research.” As Foray and Hall (2011, 6) put it, with reference to cases like the one of Pierre-Hyacinthe Caseaux, “the outcome of the process is much more than a ‘simple’ technological innovation” resulting in a new activity that offers to the regional economy “superior commercial prospects.” Additionally, our analysis can be seen as complementary to approaches focused on the roots and upstream drivers of innovation specializations, specifically concerned with the development of regional scientific strongholds (Catalán, Navarrete, and Figueroa 2020).

Second, our analysis has demonstrated that regions have different strengths in each innovation stage, and a focus on technology only overshadows opportunities for regions that do not belong to the small circle of high-tech clusters. Some regions may exploit a history of related design and market capabilities to uncover further specializations even without investing in technology (Breznitz 2021). In practice, policy makers can analyze innovation spaces to uncover patterns of cospecialization along the innovation process. They can draw much more fine-grained maps than what we could show, by leveraging the public and timely innovation metrics that we suggested here. Even though regional and national innovation scoreboards (like the EU Regional Innovation Scoreboard and the Science and Engineering indicators of the US National Science Foundation) by now include trademark and design rights counts next to patent ones, such aggregate counts can hardly characterize regional specializations in a qualitative manner and help to uncover specific strengths and weaknesses. Instead, unleashing the richness of the information on technology, design, and market classes, where local companies are filing different IPRs, allows mapping opportunities and challenges of smart specialization strategies through a relatedness lens.

Our study offers the potential for several extensions and validation exercises. A key limitation of our analysis was the coarseness of the trademark classes, which allowed us to capture market relatedness only between very broad product categories. Ongoing efforts to define more granular subclasses using text analysis of goods and service descriptions will offer the opportunity to work at the same level of detail of patent classes (Neuhäusler et al. 2021; Abbasiharofteh, Castaldi, and Petralia 2022). This will allow better alignment of empirics with the conceptual interpretation of relatedness in the market space. Another research direction would be to validate our results using alternative metrics. For instance, trademarks could be substituted with trade data, in line with how Hidalgo et al. (2007) and Pugliese et al. (2019) capture the product space. Trademark activity is likely to be related to export activity, especially when considering registrations at supranational offices like the EUIPO. Yet, trademark data also capture specializations in nontradable activities (mostly low-tech services) that will not be covered by trade data. These activities might not matter directly for innovation; still a comparison of patterns could be interesting.

Finally, our focus on NUTS-2 regions is not without limitations. There is a perennial issue noted as a modifiable areal unit problem, pointing to the fact that performing the same analysis on smaller geographic units could reveal nontrivial differences (Fotheringham and Wong 1991). Yet, an additional problem that would arise is the presence of too many zeros in the IPR metrics. A similar argument could be made for focusing on MSAs for the case of the US instead of counties or cities. Comparative analysis of different geographic levels could reveal significant insights on the implied spillovers of smart specialization policies to larger areas, an issue that has only recently been examined in the literature (Balland and Boschma 2021).

Finally, we envision the potential for several extensions of our framework. One extension could be to move beyond overall average patterns and analyze heterogeneity in how relatedness and cross-relatedness matter, for instance for economically developed ones versus lagging regions. This would align with work suggesting that the explanatory power of relatedness differs by region type (e.g., Petralia, Balland, and Morrison 2017). Alternatively, different IPR filings in urban versus rural regions might also be at play and could be controlled for (Wojan 2019). Finally, one could use our innovation space approach to zoom in on specific innovation specializations that might be particularly desirable from a strategic or societal perspective. For instance, future research could extend the rich literature on green technology specializations (e.g., Barbieri, Perruchas, and Consoli 2020) and look at relatedness dynamics for regional green innovation specializations beyond technology (in line with the firm-level analysis in Ghisetti, Montresor, and Vezzani 2021). Similarly, one could focus on the digital revolution and analyze the extent to which regions might specialize in technology, design, or market activities related to artificial intelligence or Industry 4.0. Ultimately, this goes in the direction of pushing for a broader take on regional innovation capabilities and the policies that can support them.

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