Circular Economy Transition and Recombinant Dynamics in European Regions: The Role of Localized Knowledge and Digital Technological Complementarities

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Abstract

A sustainable transition is one of the most important challenges Europe is facing. Such transition imposes an urgent need to move toward a Circular Economy (CE), calling for a deeper understanding of the relationship between innovation, technologies, and CE, which received relatively less attention in existing literature, particularly at the regional scale. This chapter contributes this debate by investigating regional recombinant dynamics in CE technologies, focusing on the role of localized knowledge, accumulated green capabilities, and the interplay with digital complementary technologies. The empirical analysis is conducted on a dataset of European NUTS2 regions over the period 1985-2015 and suggests that green and digital complementary localized capabilities increase the regional ability to absorb and integrate new technological opportunities in CE-based recombinations, representing a crucial leverage for stimulating regional transition.

1. Introduction[1]

The challenges posed by the negative consequences of climate change require collective actions aimed at reducing the environmental burden of human activities

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and favoring the transition of local economic systems to sustainable models of production and consumption. In this context, the Circular Economy paradigm has been proposed as the most promising framework to achieve the decoupling of economic development from the exploitation of limited resources (Sauvé, Bernard, Sloan, 2016; Bibas, Chateau, Lanzi, 2021). The so-called Circular Economy (CE) transition received increasing governmental support around the world to mitigate environmental pressure on the one hand and promote economic development, entrepreneurship, and employment on the other hand. The European Circular Economy Action Plan confirmed the centrality of CE in the industrial and climate policy at the European level by introducing measures and incentives to support waste management and prevention, eco-design, and markets for secondary raw materials. In order to feed the CE transition, the Action Plan acknowledges the central role of innovation and digital technologies as already recognized in the Policies and practices for the adoption of eco-innovation and the transition to the Circular Economy (EIO, 2016). As a result, academic literature has recently begun to investigate to what extent the digital transformation can increase the chances of achieving an innovation-based sustainable transition. Indeed, digital technologies can help unlock cuts in carbon emissions, increase the use of renewables and improve energy and material efficiency, thus promoting a circular economy development model. Accordingly, the label of "twin transition" has come to the fore and gained momentum in both political and academic contexts to emphasize the relevance of this phenomenon (Montresor, Quatraro, 2017; Santoalha, Consoli, Castellacci, 2021; Cicerone *et al.*, 2022).

Nevertheless, the scant evidence on the interaction between the CE and innovation dynamics (Jakobsen *et al.*, 2021) has mainly focused on individual technologies in specific CE-related domains (Barragàn-Ocaña *et al.*, 2021) or on providing a mapping of the regional innovative efforts across the full spectrum of CE technologies, describing the main actors involved, the main technological trajectories and geographical heterogeneity (Fusillo *et al.*, 2021). Yet, the regional recombinant dynamics around CE technologies remained largely unexplored.

This chapter contributes to filling this gap by studying the local recombinant dynamics behind the integration of CE knowledge and the role of existing local green and digital knowledge endowments in this regard. By opening the black box of CE-related local recombinant dynamics, this chapter makes a step forward in the understanding of such mechanisms and investigates the role of regional technological capabilities in influencing the ability to absorb and integrate new technological opportunities in the CE field. We provide evidence of the instrumental role of green knowledge in supporting the integration and exploitation of new CE recombination opportunities. Further, we delve into the crucial role of digital technologies and the exploitation of digital complementarities for recombinant regional capacities, contributing to the debate on the interaction between the sustainable and digital transformation. Lastly, we provide additional evidence on the positive effects of cognitively related knowledge bases and the regional characteristics that may complement or substitute technological relatedness. Drawing upon the literature on regional branching, we also show if and to what extent the endowment of complementary digital technologies could attenuate the stickiness of local capabilities.

Leveraging the OECD REGPAT patent database, we construct a dataset of European NUTS-2 regions observed in the period 1980-2015. The empirical analysis focuses on the regional stock of CE-technological recombination in patent citations and builds an original indicator of digital technological complementarity, together with localized knowledge endowments in the green and digital technology fields. Our results show that localized knowledge is positively associated with the recombinant capabilities of regions around CE technologies. In particular, we find that complementary digital technologies play a prominent role, suggesting that CE technologies contribute to the development of new knowledge and that their complementarity with digital technologies is functional to stimulate regional recombination activities. Our findings also show that the relatedness between CE technologies and the regional knowledge base is positively associated with CE recombinations and that complementary digital knowledge negatively moderates such relationship.

The chapter is organized as follows. Section 2 summarizes the relevant literature and introduces the conceptual framework. Section 3 presents the data and the methodology used, while empirical results are presented in Section 4. Section 5 summarizes the main findings and concludes.

2. CE, Local Recombinant Capabilities and Digital Complementarities

The CE paradigm is gaining ground as a strategy to make existing production and consumption activities more sustainable (Geissdoerfer *et al*., 2017). Indeed, the CE approach introduces closed resource loops to separate economic growth from finite resource consumption (Korhonen *et al*., 2018). It opposes the predominant linear model, based on the pattern "take-make-use-dispose", which has led to volumes of resource extraction and waste production beyond the Earth's regeneration and absorbing capacity (Murray *et al*., 2017). The CE seeks to maintain the value of products, materials, and resources for as long as possible in the economy by extending their useful life and reintroducing them in the production cycle at the end of their life (Rosa *et al*., 2019). Following the seminal work of Stahel (1994), the reuse of goods and the recycling of materials have been addressed by scholars as the foremost waste-reduction and resource-saving strategies. The former allows for the extension of the useful life of products and delays the disposal of materials, namely the *slowing* resource loop. At the same time, the latter makes the recovery of resources possible, thus *closing* resource loops (Stahel, 1994). Efficiency strategies that result in the reduction of raw materials or energy employed in an item's production, transportation, and utilization phase ultimately allow for minimizing resource consumption, hence narrowing the resource flow (Geissdoerfer *et al*., 2017).

To realize its full potential, the CE calls for a systemic change in companies, industries, and the economy through radical shifts in societal values, norms, and behaviors (Chizaryfard *et al*., 2021; Murray *et al*., 2017). In this scenario, industrial and regional systems are expected to encompass radical and systemic innovation to search for innovative and creative solutions, such as cleaner technologies, business models, infrastructures, and institutional capacity (Chizaryfard *et al*., 2021). Thus, a successful transition from a linear to a circular organization of economic activities calls for a comprehensive understanding of the relationship between innovation and CE implementation. However, despite the crucial role of innovation in designing and implementing CE practices, "the term CE is relatively absent from the innovation literature" (Jakobsen *et al*., 2021, pg. 4). The first attempt to establish a direct link between innovation and CE is represented by Jakobsen *et al*. (2021), which highlighted the "potential in applying insights from the innovation literature to provide more specific implications for how to implement the transition from a linear to a CE." (Jakobsen *et al*., 2021, pg. 4). Existing quantitative research has mostly provided insights into the evolution of single technologies applied in specific CE-related domains. Barragán-Ocaña *et al*. (2021), exploiting patent data, sought to identify the technological trajectory of wastewater reuse technologies. A study with a similar approach targeting a broader sample of CE technologies is provided by Fusillo *et al*. (2021), which map CE innovative efforts describing the main actors involved and the key technological trajectories. Yet, in this panorama, the determinants of CE technologies and the recombinant dynamics exploiting CE-related knowledge remain largely unexplored (Cainelli *et al*., 2020; de Jesus *et al*., 2018), particularly in the regional context. Cainelli *et al*. (2020) point to the role of environmental policy and green demand in driving the adoption of resource efficiency-oriented eco-innovations at the European level. However, the role on the technological background and the regional capabilities that favor the recombination of knowledge in the CE field has not been investigated yet.

Following the recombinant knowledge framework, innovation is the outcome of recombination processes, involving the novel combination of existing ideas, information, or technological components (Arthur, 2009; Kauffman, 1993; Schumpeter, 1939; Weitzman, 1998). From an evolutionary perspective, recombinant dynamics incorporate technological improvements along several paths, speeding up technical progress and sustaining technological transitions (Frenken *et al*., 2012). Limited access to knowledge sources, risk aversion, and other organizational impediments may constrain the search process through existing know-how and narrow the possibility to develop new technological knowledge (Fleming, 2001). In this context, recombinant capabilities concern the capacity of individuals to access external knowledge and to successfully manage novel recombinations (Carnabuci, Operti, 2013).

Extant geography of innovation literature has proposed the extension of the concept of innovation capabilities at the regional domain, to denote the capacity of institutions and local agents to master and coordinate systemic interactions to produce new knowledge (Cooke, 2001; Lawson, Lorenz, 1999; Quatraro, 2009; Romijn, Albu, 2002). Regional innovation capabilities are the outcome of localized knowledge interactions and exchange activities among local agents that trigger the accumulation of skills and knowledge through learning dynamics (Antonelli, 1998; Freeman *et al*., 1987). This introduces both path and place-dependent processes based on the exploitation of technological capabilities accumulated in local contexts to absorb and integrate new technological opportunities (Cohen, Levinthal, 1990; Colombelli *et al*., 2014; Henning *et al*., 2013; Martin, Sunley, 2006; Storper, 2018). Following this approach, the concept of regional recombinant capabilities has recently been proposed to indicate the ability of local innovation ecosystems to stimulate combinatorial efforts leading to the introduction of novelty (Orsatti *et al*., 2021).

Acknowledging the path-dependent dynamics of regional recombinant capabilities provides a fertile ground for the analysis of local innovation processes in the CE domain. In this direction, the extant literature allows for the identification of three main enabling channels influencing the capacity to engage in CE-based recombinations at the local level, i.e., green technological capabilities, digital complementarities, and technological relatedness. For what concerns green technological capabilities, extant literature has stressed the impact of previous experience in green innovation dynamics for the further generation of novelties in this domain (Orsatti *et al*., 2020). In the context of CE-related technological change, de Jesus *et al*. (2018) have stressed the instrumental role of environmental innovation (EI) in achieving the CE objectives. More recently, microeconomic evidence has shown that CE solutions appear to depend more on existing technologies that address systemic innovations rather than on radical innovations. Moreover, a firm's technological capabilities and knowledge sourcing from diverse networks have proven to be essential in fostering the production of circular eco-innovation and creating a competitive advantage (Demirel, Danisman, 2019; Kiefer *et al*., 2021; Triguero *et al*., 2022). In this direction, established capabilities in green technological change can be a source of competitive advantage in CE-based recombinations, in view of their reliance on diversified knowledge bases stemming from the integration of diverse and heterogeneous knowledge sources, requiring different and heterogeneous technology fields and skills (Barbieri *et al*., 2021; De Marchi, 2012; Fusillo, 2020; Fusillo *et al*., 2022; Petruzzelli *et al*., 2011). Based on this discussion, we hypothesize that the extent to which regions are able to integrate and exploit new recombination opportunities in the CE field depends on the technological capabilities in the green domain accumulated within regional knowledge bases.

Extant literature also pointed to digital technologies as essential enablers of circular innovation and practices implementation within businesses (Bag *et al*., 2020; Chauhan *et al*., 2022; Ranta *et al*., 2021). The European Eco-Innovation Observatory has first recognized the importance of EI in carrying out the transition from a linear to a circular economic system (EIO, 2016) and, more recently, the role of digitalization and artificial intelligence as an accelerator of energy and resource optimization (EIO, 2021). Digital technologies are critical to manage the increasing amount of knowledge and information flows captured and transferred among companies, to track products and materials, and, ultimately, to improve the efficiency of production and distribution processes (Salvador *et al*., 2021). Pagoropoulos, Pigosso, and McAloone (2017) illustrate the grouping of digital technologies in three classes based on their function: data collection, data integration, and data analysis. Data collection technologies include sensors (e.g., radio frequency identification) and devices that connect products and users to the Internet (e.g., the Internet of things). These technologies are crucial to reveal inefficiencies in extant business models and production methods and, thereby, support the production process optimization and the value chain management (Ranta *et al*., 2021). Data integration and data analysis technologies (e.g., Artificial Intelligence (AI) tools and techniques or Big Data analytics) format and process huge amount of data to provide information (Pagoropoulos *et al*., 2017). Digital technologies play a key role in driving the shift toward novel business models, such as hybrid product–service solutions (PSS) and pay-per-usage models (Chauhan *et al*., 2022; Pagoropoulos *et al*., 2017). Indeed, IoT technologies gather data and inform the owner on the location and maintenance status of a set of items. The ability to track the connected items ease the access from a multitude of users, and data collected are employed to improve their durability, preventing premature breakdowns, and thus slowing resource flows. The digitalized systems are finding more and more applications also in the waste management sector, crucial to achieve CE objectives, in form of sensors for material detection or robotic technologies for sorting of mixed waste (Sarc *et al*., 2019).

Because of their enabling role and their broad applicability across domains, digital technologies and AI are assimilated to General Purpose Technology (GPT) (Trajtenberg, 2019). GPT have been found to widen the scope for knowledge search and move the technological frontier, allowing local systems to exploit complementarities across knowledge domains and introduce new and unprecedented recombinations (Bresnahan, Trajtenberg, 1995; Capello, Lenzi, 2021). Regional scholars have widely confirmed the role of GPTs and their new generation, i.e., the Key Enabling Technologies (KETs), on the regional ability to open new technological diversification paths (Montresor, Quatraro, 2017). The local endowment of KETs in general, and of AI in particular, has been also found to increase the likelihood of regional technological diversification in the green domain (Montresor, Quatraro, 2020), though AI seems to favor regions already possessing sound green technological specializations (Cicerone *et al*., 2022). These considerations suggest that the transition to a circular economy could greatly benefit from the potentiality of digital technologies to integrate multiple and technologically dispersed knowledge bits. Accordingly, the localized endowment of digital technologies can be seen as promising tools to foster recombinant dynamics leveraging on CE-related technologies. Yet, the wide spectrum of digital technologies may reveal high differences in the extent to which they connect knowledge bases and favor successful recombination (Martinelli *et al*., 2021). Circular strategies rely on timely and effective data management and sharing, the optimization of energy and material usage in both the production and utilization phase, the management of forward and reverse logistics. Thus, technologies for data collection, storage and processing, and digital communication may provide regions with specific but complementary digital capabilities instrumental to the absorption and recombination of new CE-related knowledge. The role of complementary capabilities is gaining increasing attention in technology and regional studies. For example, complementary capabilities have been shown to play a key role in preventing regions from ending up in a lock-in situation (Balland, Boschma, 2021a). Balland and Boschma (2021a) further argue that a new technology has a higher probability to enter a region when the latter has access to complementary capabilities for this new technology provided by other regions. By focusing on green technologies, Barbieri *et al*. (2021) shows that their development also depends on improvements in non-green but complementary technological areas. Along these lines, we hypothesize that localized cumulated knowledge in digital complementary technologies allow regions to integrate new technological opportunities within knowledge bases, favoring regional recombinant capabilities around CE-related knowledge.

Finally, evolutionary economic geography literature recognizes technological relatedness as another key driver for the success of new knowledge recombinations (Balland *et al*., 2019; Boschma, 2017). According to the relatedness framework, the recombination of knowledge is more likely to take place the more the components are related to each other from a technological perspective (Neffke *et al*., 2011; Tanner, 2014). This suggests that knowledge recombination is shaped by the similarity between pre-existing local knowledge base and the new technological knowledge.

Accordingly, high levels of cognitive proximity between the extant knowledge bases and the new technological knowledge may increase the absorptive capacity and ease the assimilation of such new knowledge. Recent contributions highlighted the importance of relatedness in sustaining regional specialization in specific technological domains, such as renewable energy (Moreno, Ocampo-Corrales, 2022). Within the European landscape Santoalha and Boschma (2021) show that new specializations in green technologies are more likely to occur in regions with related technologies. Perruchas, Consoli, and Barbieri (2020) obtained similar results on a worldwide sample at the country level. Montresor and Quatraro (2020) add that the regional entry of new green technologies is driven by the relatedness to the pre-existing technologies that are both green and non-green. Balland and Boschma (2021b) and Corradini, Santini, and Vecciolini (2021) find that the knowledge around industry 4.0 technologies (I4T) is more likely to thrive in regions with local capabilities in I4T- related technologies. Based on this background, we expect that regions endowed with pre-existing knowledge bases related to the CE technological domain are better able to integrate new knowledge based on CE-related technological advancements into their recombinant innovation activities.

Building on the relatedness framework, an emerging body of research identified a broad set of regional factors that may substitute or complement the role of relatedness (Castellani *et al*., 2022; He, *et al*., 2018; Montresor, Quatraro, 2017). These factors may attenuate the cognitive constraints that being close to the existing knowledge base may pose to the recombination and development of new and/or unrelated technologies (Elekes *et al*., 2019; Miguelez, Moreno, 2018; Neffke *et al*., 2018; Zhu *et al*., 2017). Because of the enabling role of digital capabilities to connect distant but complementary knowledge domains and ease the exploitation of recombination opportunities, digital complementary capabilities could hinder lock-in effects triggered by related paths, enabling regions to overcome the stickiness of local capabilities. Thus, we expect that the local endowment of digital complementary cumulated knowledge negatively moderates the constraining role of CE technological relatedness. In other words, larger stocks of digital complementary knowledge provide regions with an asset allowing CE-related recombinant dynamics to span areas of the technology landscape that are loosely related cognitively to one another.

3. Empirical Analysis

3.1. Circular Economy Technologies

In order to investigate the knowledge recombination dynamics of CE technologies, we exploit patent data extracted from the OECD REGPAT database, March 2020, collecting information on patent applications at the European Patent Office (EPO) published between 1980 and 2015. We also make use of the OECD Citation Database, March 2020, to retrieve all the citations in the EPO and PCT patent documents.[2]

Relying on the well-grounded and widely accepted classification provided by the European Commission, we first identify patents related to the CE. Precisely, the EC provides a list of technological classes, following the Cooperative Patent Classification (CPC) code, in the set of Circular Economy indicators to monitor progress toward a circular economy on the thematic area of competitiveness and innovation.[3] The list encompasses technological codes belonging to the subclass Y02W on "Climate change mitigation technologies related to wastewater treatment or waste management". Accordingly, we classify as Circular Economy related those patents assigned to at least one of these technology fields. Thus, in line with recent literature, the focus is on the development of techniques for the collection, reduction, and recycling of waste, water, and materials aimed at reducing the dependence on critical commodities while improving economic resilience (Cainelli *et al.*, 2020). The identified set of CE patents consists of 6,407 patents from 1980 to 2015, for which at least one inventor resides in a European country. Inventors' addresses, provided at NUTS2 regional level, have also been used to assign patents to regions and measure their inventive activity. For co-invented patents with listed inventors residing in multiple regions, patent applications are proportionally allocated to regions applying fractional counting.

3.2. Variables and Methodology

The set of identified CE-related patents is employed to build the dependent variable. Our dependent variable is, thus, a measure of the regional stock of CE-related knowledge recombination. Precisely, considering the purpose of our analysis and the still limited number of CE patents, we measure CE recombinations by counting the number of patents that cite at least one circular patent in the backward citations of a region's patenting portfolio. To avoid year-to-year fluctuations in the number of patents and account for the cumulated knowledge, providing a deeper insight into the phenomenon at stake, we make use of a stock variable. The stock of CE knowledge recombinations (*CE recomb*) is computed

2. It is worth stressing that, notwithstanding the well-known drawbacks in the use patent data (Griliches, 1998), they are one of the most effective sources to explore regional inventive activities as they provide a wealth of granular information on the location, time, and technologies of such activities (Jaffe, Trajtenberg, 2002; Strumsky *et al.*, 2012).
3. The European Commission CE monitoring framework is available at ec.europa.eu/eurostat/web/circular-economy.

using the perpetual inventory method (PIM), calculated as the cumulative stock of CE citing patents by region, applying a yearly rate of obsolescence of 15%.[4]

Our first explanatory variable is the overall regional knowledge stock (*K Stock*) that accounts for the region's absorptive capacity and is expected to affect the ability of regions to recombine CE technologies. The regional stock of knowledge is calculated by applying the PIM method to the whole regions' patent portfolios. Secondly, to account for the localized endowment of green and digital technological capabilities two independent variables are built. As for the former, the cumulated know-how in the green technological domain is measured as the stock of patents with at least one backward citation toward green patents (*GT Stock*). Green-tech patents are identified following the OECD ENV-TECH classification (Haščič, Migotto, 2015), which provides the list of technological classification codes associated to the environmental domain based on the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).[5] Concerning the cumulated localized knowledge in the digital domain, we classify as digital those patents that are assigned to at least one technology class covered by the electrical engineering area as in the classification proposed by Schmoch (2008). Given our interest in the role of complementary digital capabilities in regions and that we expect the enabling role of digital technologies in the recombination of CE knowledge to be proportional to the extent of complementarity between the two fields, we first calculate the degree of complementarity, for each digital technology, with respect to CE related technologies. To do so, we identify those patents co-classified in both CE and digital technologies and then, for each digital technology, we calculate the relative frequency with which they co-occur in the joint CE-digital patents. Then, the relative co-occurrence frequency, representing our proxy for the degree of complementarity, is employed to compute the stock of patents citing digital patents for each region, which is weighted by the degree of complementarity of the corresponding digital technology (*DG compl Stock*). Table 1 reports a list of the top 10 digital technologies ranked by their degree of complementarity with the CE technologies.

To capture the cognitive proximity between regions' existing technological capabilities and CE-related knowledge, we construct a measure of the CE technological relatedness (*CE rel*). Following consolidated existing literature, to measure CE relatedness we, first, exploit the co-occurrence of 4-digits CPC classes in patent documents to calculate the degree of proximity between each

4. The literature includes several attempts to estimate the patent depreciation rate without conclusive evidence (Pakes, Schankerman, 1979; Schankerman, 1998). In this work, we set the obsolescence rate at 15%, which is the most frequent value employed in the literature (see among others Hall *et al*., 2005; Keller, 2002; McGahan, Silverman, 2006; Nesta, 2008).

5. For the sake of consistency between technological classification, IPC codes are converted into CPC codes by exploiting the concordance tables available at cooperativepatentclassification.org.

Table 1 – Top Digital Complementary Technologies

CPC	*Technology*	*Complementarity*
H01M	Processes or means, e.g., batteries, for the direct conversion of chemical into electrical energy	0.4533
G06Q	Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes	0.1705
H01J	Electric discharge tubes or discharge lamps	0.1380
H01B	Cables	0.0419
H05K	Printed circuits	0.0379
G06K	Recognition of data	0.0325
G11B	Information storage based on relative movement between record carrier and transducer	0.0257
H05B	Electric heating	0.0257
F21V	Functional features or details of lighting devices or systems thereof	0.0230
G06F	Electric digital data processing	0.0230

Source: Authors' elaboration

technology *s* and *c* at time *t*. We define proximity as the minimum pairwise conditional probability of a region having a Revealed Technology Advantage (RTA) in technology *s* given that it has a specialization (RTA) in another technology *c*. In the second step, we calculate the relatedness density of each technology *s* with respect to all technologies *c* in which region *r* has an RTA. Lastly, we select the technology-specific relatedness by filtering the density value corresponding to the CE technology, thus obtaining a measure of the region *r* average relatedness density around CE-related knowledge.

Our baseline specification focuses on the role of overall localized knowledge (*K Stock*) and is expressed by the following equation:

$$CErecomb_{r,t} = \beta_0 + \beta_1 KStock_{r,t-1} + \beta_2 CErel_{r,t-1} + \beta_3 GDPpc_{r,t-1} + \gamma_r + \delta_t + \epsilon_{r,t} \quad [1]$$

where *r* denotes the region and *t* the time period consisting of 5-years time intervals from 1980 to 2015. *CE rel* is our measure of the CE technological relatedness, and *GDP pc* is the regional gross domestic product (GDP) per capita introduced as a control to account for the level of economic development in a region.[6] Region (γ_r) and time (δ_t) fixed effects are also included in the model to account for region-specific time-invariant unobservables and to adjust for common shocks in the period of analysis. $\epsilon_{r,t}$ is an idiosyncratic error term.

6. GPD and population data are extracted from Eurostat.

In the second specification, the role of the stock of green and digital complementary technologies is estimated (respectively *GT Stock* and *DG compl Stock),* yielding the following model:

$$CErecomb_{r,t} = \beta_0 + \beta_1 GTStock_{r,t-1} + \beta_2 DGcomplStock_{r,t-1} + \\ + \beta_3 CErel_{r,t-1} + \beta_4 GDPpc_{r,t-1} + \gamma_r + \delta_t + \in_{r,t} \qquad [2]$$

Lastly, to investigate the moderating role of complementary digital knowledge on CE-specific relatedness in affecting regional CE technological recombinations, we extend model in equation 2 by introducing an interaction term as follows:

$$CErecomb_{r,t} = \beta_0 + \beta_1 GTStock_{r,t-1} + \beta_2 DGStock_{r,t-1} + \beta_3 CErel_{r,t-1} + \\ + \beta_4 DGcomplStock_{r,t-1} * CErel_{r,t-1} + \beta_5 GDPpc,_{rt} + \gamma_r + \delta_t + \in_{r,t} \qquad [3]$$

Models in equations 1-3 are estimated by using two-way panel fixed effects regressions estimated using OLS. In all specifications, we apply the natural logarithm transformation to adjust for the skewed distribution of the continuous variables and cluster standard errors at the NUTS2 level to account for heteroskedasticity. We further lag explanatory variables by one period. Summary statistics of the variables employed in the models are reported in Table 2.

4. Results

Figures 1 and 2 offer a graphical visualization of the geographic distribution by NUTS2 regions of, respectively, the stock of CE-based recombinations and the stock of digital complementary technologies, over the period 1980-2015. Regions are colored according to the quintile rank of the distribution, where darker colors indicate higher quintiles. Both figures highlight a heterogeneous distribution across European NUTS2 regions, showing that CE recombinant activities and the cumulated digital complementarity capabilities are more concentrated in Central Europe regions (i.e., Germany, northern Italy, Austria, and southern France) with a marked difference with Eastern European regions.

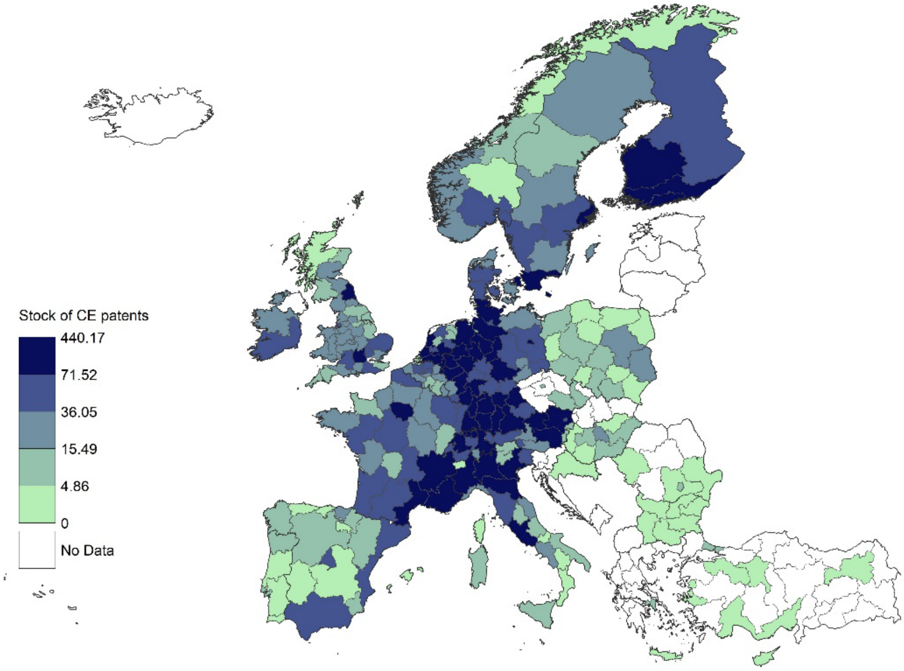
Results of the regression analysis are presented in Tables 3 and 4. Column 1 of Table 3 report the results of our baseline specification where *K Stock* and *CE rel* are the focal regressors. The estimated coefficient of the overall knowledge stock is positive and statistically significant, suggesting that the cumulated regional knowledge capabilities and absorptive capacity are associated with successful recombination dynamics involving CE-related technologies that facilitate the development of new knowledge. Column 1 also shows that the *CE rel* estimated coefficient is positive and significant, suggesting that having technological

Table 2 – Summary Statistics

Statistic	*N.*	*Mean*	*St. Dev.*	*Min*	*Max*
CE recomb	1763	238.790	441.263	0.000	4.401.709
K Stock	1763	21.128.590	46.620.510	0.125	590.953.400
GT Stock	1763	2.979.278	7.350.063	0.000	101.469.600
DG Stock	1763	6.568.777	18.052.360	0.000	240.082.400
DG compl Stock	1763	218.665	601.338	0.000	8.125.498
DG non-compl Stock	1763	6.350.112	17.469.140	0.000	231.956.900
CE rel	1925	0.1600	0.1202	0.000	0.4620
GDPpc	1685	184.667.700	146.655.200	4.528.554	223.603

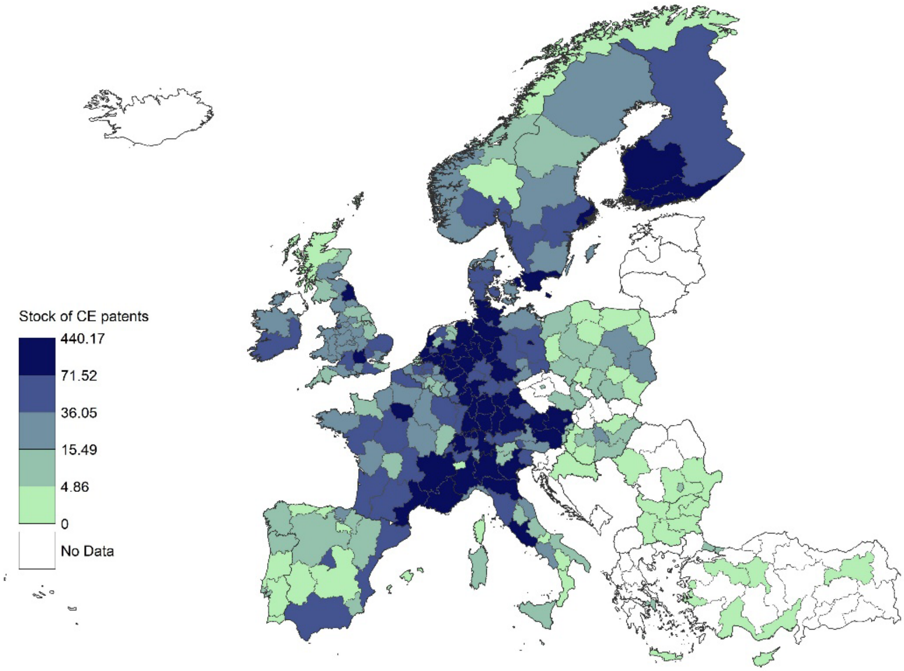
Source: Authors' elaboration

Figure 1 – Geographic distribution of the cumulated stock of CE citing patents by European NUTS2 regions, from 1980 to 2015



Source: Authors' elaboration

Figure 2 – Geographic distribution of the cumulated stock of digital complementary citing patents by European NUTS2 regions, from 1980 to 2015



Source: Authors' elaboration

capabilities in domains related to the CE positively contributes to the recombination of circular knowledge and the generation of new technological knowledge.

Model 2 focuses on the role of localized capabilities in the green and digital domains underlying the contribution of complementary digital technologies. The estimation result presented in column 2 shows that the cumulated know-how in both the green and complementary digital fields is positively associated with regions' ability to develop new technologies leveraging the recombination of the CE-related knowledge. This finding suggests that regions endowed with cumulated capabilities in green and digital complementary technologies are better able to activate positive dynamics of circular knowledge recombination and consequent knowledge creation. Since the knowledge developed within the two fields that characterize the so-called "twin transition" is successfully assimilated and exploited in new technologies developed through the recombination of circular knowledge, this result provides intriguing evidence on the importance of knowledge development progresses to speed up the transition from a linear to a sustainable circular economy model.

Table 3 – CE Recombinations and Localized Knowledge

	-1	*-2*	*-3*
K Stock	0.1669*** (0.0473)		
GT Stock		0.2027*** (0.0438)	0.1680*** (0.0452)
DG compl Stock		0.1468*** (0.0406)	0.3202*** (0.0669)
CE rel	3.9507*** (0.4871)	2.9141*** (0.4624)	3.3805*** (0.4894)
DG compl Stock * CE rel			-0.4877*** (0.1607)
GDPpc	0.1353* (0.0782)	0.2793*** (0.0768)	0.2564*** (0.0748)
Constant	-1.2004* (0.6508)	-2.1019*** (0.6473)	-1.8933*** (0.6291)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
Observations	1,345	1,345	1,345
R^2	0.9678	0.9696	0.9701
Adjusted R^2	0.9605	0.9627	0.9633
F Statistic	1.321.080***	1.397.456***	1.413.745***

Notes: Dep var: regional stock of patents citing CE-related technologies. Explanatory variables are log transformed and lagged by one year. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01.

Source: Authors' elaboration

The hypothesized moderating role of the complementarity between digital and circular technologies on the relationship between CE relatedness and CE recombinant activity is estimated in column 3 of Table 1. The coefficient of the interaction between *DG compl Stock * CE rel* is negative and significant, suggesting that complementary digital capabilities might attenuate the importance of CE relatedness. If, on the one hand, the recombination of pre-existing CE knowledge is facilitated by the cognitive proximity of regions' knowledge bases with the CE technologies, on the other hand, it is the complementarity with the digital knowledge that makes the former prerequisite less important. Indeed, the cumulated competences in the digital field complementary to the circular one might enable regions to develop new knowledge as a result of the CE knowledge recombinations, making the generation process of new technological solutions more accessible to regions that have a knowledge base less cognitively close to the CE field. Then, digital

Table 4 – CE Recombinations, Localized Knowledge and Digital Complementarities

	-1	*-2*	*-3*
GT Stock	0.1900***	0.1816***	0.1675***
	(0.0511)	(0.0483)	(0.0484)
DG Stock	0.0745*		
	(0.0399)		
DG compl Stock		0.1365***	0.3192***
		(0.0428)	(0.0777)
DG non-compl Stock		0.0428	0.0013
		(0.0406)	(0.0436)
CE rel	29842***	27995***	33751***
	(0.4896)	(0.4560)	(0.5044)
DG compl Stock * CE rel			-0.4858***
			(0.1740)
GDPpc	0.1767**	0.2632***	0.2560***
	(0.0745)	(0.0806)	(0.0783)
Constant	-1.3600**	-1.9809***	-1.8904***
	(0.6415)	(0.6755)	(0.6529)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
Observations	1,345	1,345	1,345
R^2	0.9691	0.9697	0.9701
Adjusted R^2	0.9620	0.9627	0.9632
F Statistic	1.370.300***	1.393.549***	1.406.849***

Notes: Dep var: regional stock of patents citing CE-related technologies. Explanatory variables are log transformed and lagged by one year. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: Authors' elaboration

complementary knowledge not only contributes to the development of new technological knowledge in a direct way, but it also allows to overcome the risk of the lock-in path due to relatedness.

In light of the results presented so far, we expect that it is not the endowment of digital technologies per se that is conducive to CE recombination but rather its complementarity with CE technologies. To highlight the role of complementarity, we estimate models 2 and 3 by distinguishing between the stock of non-complementary digital technologies and the stock of the complementary ones. Results of these additional estimations are presented in Table 4. Column 1 reports our baseline specification, where the overall stock of digital technologies (both complementary and non-complementary) is included. We estimate a positive coefficient for the *DG stock* variable, though modest in magnitude and statistical significance. In line with our previous findings, the estimated coefficient of the digital complementary knowledge stock is still positive and statistically significant in columns 2 and 3 of Table 4. Interestingly, we find a non-significant role of the stock of non-complementary digital technologies on the regional ability to recombine circular knowledge, as indicated by the non-significant estimated coefficient of *DG non-compl Stock*. Lastly, the role of complementary digital technologies in attenuating the relatedness of CE knowledge is also confirmed.

5. Conclusions

Building on the geography of innovation literature, this chapter investigated the role of cumulated knowledge capabilities in a regional context on the recombination of localized knowledge in the increasingly relevant and promising field of the Circular Economy. Although governments and institutions worldwide are adopting and implementing CE practices in industrial and economic policies and strategies, aiming at shifting from a linear to a circular economic model, innovation and regional studies have posed little attention to the innovative dynamics leading to the generation and exploitation of CE related technologies. Specifically, systematic evidence on the mechanisms that facilitate the regional recombinant dynamics around circular technologies and lead to the development of new knowledge is still missing. By exploiting a sample of European NUTS-2 regions over the period 1980- 2015, our analysis aims at providing new evidence on the relationship between localized knowledge capabilities and the successful recombination of CE-related knowledge that leads to the generation of new knowledge. We show that the endowment of cumulated green knowledge and digital knowledge complementary to the circular one facilitates regional recombination processes of CE-related technologies. Our findings suggest that the know-how at the heart of the envisaged twin-transition, together with the importance of complementary digital capabilities, might enable regional recombination dynamics of circular knowledge, that can accelerate the achievement of a sustainable transition.

These results contribute to the existing literature in two major ways. First, opening the black box of the mechanisms behind the generation of new knowledge by means of the recombination of circular technology, we highlight the crucial role of local cumulated capabilities in European regions. We make a step forward in the understanding of regional recombinant dynamics and show that green-digital local capabilities are essential to trigger continuous knowledge improvements accelerating the path toward a sustainable transition. Further, we contribute the debate on the "twin-transition" in regional economies by showing that the enabling role of digital technologies in integrating multiple knowledge bits, dispersed in the technology space, is more effective when regions are endowed with digital technological capabilities that are complementary to the circular field.

This chapter also contributes the public debate in term of policy implications. Designing instruments to sustain regional innovative activities directing them toward green and digital technologies and reinforcing the existing local knowledge capabilities could be a leverage for the elaboration of strategies promoting research and innovation in the CE domain and the successful integration of circular knowledge in technological advancements. This implies the need to strengthen the institutional frameworks providing policy tools and incentives that facilitate the effective transfer of technological capabilities acquired in green and digital complementary fields, stimulating localized spillovers. Moreover, fostering the identification and generation of digital complementary technologies requires the design of strategic policies aimed at supporting the exploitation of knowledge hybridization, complementarities, and spillover between CE and digital capabilities. Lastly, policy efforts supporting the creation of positive network dynamics among regional actors might be crucial to sustain the development and integration of different and complementary skills and competences.

This study presents some limitations. First, we acknowledge that the classification of CE patents provided by the EC, being mainly focused on wastewater treatment or waste management, may only represent a subset of the potential technology advancements in the fields. At the same time, we rely on the efforts put forth by the European Commission in the CE monitoring framework in order to avoid subjectivity and facilitate comparison with other studies. A second limitation is related to the emphasis put on the codified side regarding the CE knowledge that may come at the cost of underestimating the broad introduction and adoption of CE practices. Nevertheless, given the increasing concerns about the need to understand innovation processes for a sustainable CE transition, recent contributions in the literature highlighted that while innovation activities in CE are still in the development phase, the wide potential of knowledge advancements and the recombination opportunities make the search for radical solutions for a successful CE transition increasingly reliant on technological efforts.

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Transizione Circolare e dinamiche ricombinatorie nelle regioni europee: il ruolo della conoscenza localizzata e della complementarietà tecnologica digitale

Sommario

Il raggiungimento di una transizione verde e sostenibile è una delle principali sfide che l'Europa sta affrontando. Tale transizione impone la necessità di muoversi sempre più verso un'Economia Circolare (CE). Questo richiede una maggiore comprensione della relazione tra innovazione, tecnologie e CE che ha ricevuto relativamente meno attenzione nella letteratura esistente, soprattutto a livello regionale. Questo capitolo si inserisce in questo dibattito e si pone l'obiettivo di esplorare le dinamiche di ricombinazione delle tecnologie CE a livello regionale, concentrandosi sul ruolo della conoscenza localizzata, delle capacità accumulate nel dominio tecnologico green e della complementarità con le tecnologie digitali. L'analisi empirica è condotta su dati raccolti per le regioni europee (NUTS2) tra il 1985-2015 e suggerisce che le capacità localizzate green e digitali complementari favoriscono la capacità delle regioni di assorbire e integrare nuove opportunità tecnologiche in ricombinazioni basate su tecnologie circolari, rappresentando quindi un importante stimolo verso una transizione sostenibile in ambito regionale.