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LEVERAGING ON CIRCULAR ECONOMY TECHNOLOGIES FOR RECOMBINANT DYNAMICS: DO LOCALIZED KNOWLEDGE AND DIGITAL COMPLEMENTARITIES MATTER?

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Leveraging on Circular Economy technologies for recombinant dynamics: do localized knowledge and digital complementarities matter?

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ABSTRACT

This paper investigates the relationship between local knowledge bases and recombinant dynamics in CE technologies. We focus on the role of accumulated green and digital complementary capabilities and posit that they are positively associated to regional ability to absorb and integrate new technological opportunities in CE-based recombinations. The empirical analysis, conducted on a dataset of European NUTS2 regions over the period 1985-2015, suggests that both green and digital complementary localized capabilities represent crucial leverage for regional recombinant activities around CE technologies.

KEYWORDS

Circular Economy; twin transition; regional recombination capabilities; localized knowledge; digital technologies

JEL CLASSIFICATION

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1. Introduction

The Circular Economy (CE) paradigm is globally gaining ground as a strategy to make existing production and consumption patterns more sustainable (Geissdoerfer et al., 2017). 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 extends the useful life of products and delays the disposal of materials – the *slowing* resource loop. The latter makes the recovery of resources possible, thus *closing* resource loop (Stahel, 1994). The CE approach introduces closed resource loops in an effort to separate economic growth from finite resource consumption (Korhonen, Honkasalo, & Seppälä, 2018). It opposes the predominant linear model, based on the "take–make–use–dispose" pattern, that led to resource extraction and waste production volumes beyond the Earth's regeneration and absorbing capacity (Murray, Skene, & Haynes, 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, Sassanelli, & Terzi, 2019). Efficiency strategies that reduce 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). The CE paradigm has also been subject to some critiques, pointing to underestimating the potential "rebound effects" of CE practices, on the one hand, and overestimating CE solutions as a panacea for addressing sustainable development (Castro et al., 2022; Corvellec et al., 2022).

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, Trucco, & Nuur, 2021; Murray et al., 2017). In this scenario, industrial and regional systems are expected to encompass radical and systemic innovation to search for new and creative solutions, such as cleaner technologies, innovative business models, infrastructures, and institutional capacity (Chizaryfard et al., 2021). Thus, the urgent need for a successful transition from a linear to a circular organization of production and economy calls for a comprehensive understanding of the relationship between innovation and CE implementation (De Jesus & Mendonça, 2018).

However, despite the crucial role of innovation in designing and implementing CE transition strategies, the literature focusing on this nexus is still underdeveloped (Jakobsen et al., 2021). Former quantitative research has analyzed the innovation for the CE transition within the conceptual and methodological framework of the eco-innovation literature (Barbieri et al., 2016). On the one hand, existing studies provide insights into the evolution of single technologies applied in specific CE-related domains. For example, Barragán-Ocaña, Silva-Borjas, and Olmos-Peña (2021) sought to identify the technological trajectory of wastewater reuse technologies by exploiting patent data. At the same time, few studies dealt with the firm-level drivers of CE innovation adoption, focusing on the role of demand-side factors and environmental regulation (Cainelli, D'Amato, & Mazzanti, 2020; de Jesus et al., 2018; De Jesus & Mendonça, 2018).

Within this context, the geography of innovation literature has largely neglected the study of innovation dynamics related to the CE transition. This is quite an important gap, as the heterogeneity of places in terms of skills and capabilities likely affects the development of CE-related trajectories (Fusillo, Quatraro, & Santhià, 2021), and uneven spatial evolutionary patterns can be a source of inequalities within and across regions. This paper aims to fill this gap by looking at European regions' innovation patterns in the CE domain. In doing so, we adopt a recombinant knowledge perspective (Weitzman, 1998) and implement an analysis of the drivers behind the generation of new technologies recombining CE-related knowledge.

We follow the growing literature on the so-called twin transition that shows how digitalization can increase the chances of achieving an innovation-based green transition (Cicerone et al., 2022; Montresor & Quatraro, 2020; Santoalha, Consoli, & Castellacci, 2021). Recent technical and academic studies stressed the potential of digital technologies for the unlocking of carbon emissions cuts, boosting the use of renewables, and improving energy and material efficiency, thus promoting a CE model (Huynh & Rasmussen, 2021; Ranta, Aarikka-Stenroos, & Väisänen, 2021; Rusthollkarhu, Ranta, & Aarikka-Stenroos, 2021). Moreover, given their general purpose nature, digital technologies can also play a bridging role between different technological domains and hence ease recombinant dynamics, above all when green technologies, like those enabling the CE transition, are at stake (Montresor & Quatraro, 2017, 2020).

Our empirical analysis is based on a sample of European NUTS-2 regions observed over 1980-2015 and focuses on the regional stock of CE-related technological recombination in patent citations. By exploiting European patent data, we construct a novel indicator of digital technological complementarity with the CE domain and build localized knowledge endowments in the green and digital complementary technology fields. Our results show that the endowment of green and digital technological knowledge is positively associated to regional recombinant activities around CE technologies. We also find that the relatedness between the CE technologies and the regional knowledge base is associated with CE recombinations at the local level and that the complementary digital capabilities negatively moderate the role of CE relatedness. Our findings suggest that circular technologies not only contribute to the roll-out of new knowledge but also that their complementarity with digital technologies is functional to regional recombinant activities. Lastly, we investigate the specific role of cumulated capabilities in different technological sub-fields. Out of the green ones, we find a more pronounced relevance of climate change adaptation technologies compared to mitigation technologies. Concerning the digital field, a greater relevance of complementary computer technologies, digital communication, and IT methods technology fields is found.

These findings contribute to the economic geography literature by opening the black box of CE-related local recombinant dynamics. We make a step forward in understanding such mechanisms by investigating the role of existing technology-specific capabilities in influencing the ability to absorb and integrate new technological opportunities in the CE field. First, we provide evidence of the instrumental role of green knowledge in sustaining the integration and exploitation of new recombination opportunities in the CE field. Secondly, we contribute to the debate on the interplay between green and digital transformation by pointing to the crucial role of digital technologies and the exploitation of digital complementarities for regional recombinant capabilities. Lastly, drawing upon regional branching literature, we provide additional evidence on the positive effects of cognitively related regional knowledge bases and the role of regional characteristics in complementing or substituting technological relatedness, studying whether the endowment of digital complementary technologies might attenuate the stickiness of local capabilities.

The remainder of the paper is organized as follows. Section 2 provides the conceptual framework and reviews the relevant literature. Section 3 presents the data and the methodology employed in the study, while results are presented and discussed in Section 4. Section 5 concludes.

2. Conceptual framework

2.1. Localized recombinant capabilities, relatedness, and the CE transition

The deep transformation of the techno-economic structure implied by the transition to the CE paradigm makes innovation intrinsic to this process. The understanding of the CE transition can hence benefit from the extension of the innovation studies literature, and specifically of the eco-innovation conceptual and empirical framework of analysis (De Jesus & Mendonça, 2018).

Within the Schumpeterian stream of literature, an established tenet concerns the conceptualization of the innovation process as an outcome of individuals' capacity to combine ideas and technology in new ways (Schumpeter, 1934). This has originated a fertile domain of research that has articulated an analytical framework known as *recombinant knowledge approach*, according to which discoveries and innovations are the outcomes of combinatorial dynamics involving the novel combination of existing ideas, information, or technological components (Arthur, 2009; Kauffman, 1993; Weitzman, 1998). From an evolutionary perspective, recombinant dynamics incorporate technological improvements along several paths, speeding up technical progress and sustaining technological transitions (Frenken, Izquierdo, & Zeppini, 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 of developing new technological knowledge (Fleming, 2001). Based on these grounds, recent literature grafted the recombinant knowledge approach onto the analysis of innovation capabilities. The concept of *recombinant capabilities* has hence been proposed to indicate agents' capacity to access external knowledge and manage novel recombinations successfully (Carnabuci & Operti, 2013; Orsatti, Quatraro, & Pezzoni, 2020).

At the regional level, innovation capabilities denote instead 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). Accordingly, *regional recombinant capabilities* refer to the presence in local contexts of individuals and organizations able to manage combinatorial efforts leading to the introduction of novelty (Orsatti, Quatraro, & Scandura, 2021).

An increasing number of studies have framed the analysis of eco-innovation generation focusing on recombinant capabilities (Barbieri, Marzucchi, & Rizzo, 2020; Orsatti et al., 2020; Quatraro & Scandura, 2019; Zeppini & van den Bergh, 2011)., highlighting various specific characteristics of eco-innovation processes. For instance, Zeppini and van den Bergh (2011) proposes a model in which the generation of Green Technologies (GTs) is based on combining diverse and loosely related elements from the knowledge space. Combining highly heterogeneous technological components is more likely to lead to a paradigm shift from a traditional (non-green) regime to a cleaner one (Fleming, 2001; Nightingale, 1998). Furthermore, numerous studies utilizing patent data indicate that GTs exhibit higher technological complexity than conventional technologies and that the recombination of technological elements they rely on is often novel or infrequently attempted before (Barbieri et al., 2020; Fusillo, 2023; Messeni Petruzzelli, Maria Dangelico, et al., 2011; Orsatti, Quatraro, & Scandura, 2023).

The diffusion and integration of green technologies into existing production techniques are necessary to observe an actual impact on environmental performance.

Adopting a recombinant perspective on CE innovation allows for appreciating the diffusion of CE technologies and their contribution to further developing new technologies by looking at how new knowledge builds on and combines existing CE-related knowledge (Barbieri et al., 2020; Hall & Helmers, 2013).

Yet, regional knowledge integration and recombination capabilities are constrained by the cognitive proximity between the knowledge to be combined and local innovating agents' knowledge base. The evolutionary economic geography literature has stressed this aspect and showed that technological relatedness represents a crucial factor affecting the success of new knowledge recombination in local contexts (Balland et al., 2019; Boschma, 2017; Montresor & Quatraro, 2017).

According to the relatedness framework, the recombination of knowledge is more likely to occur when the components are close to each other in the knowledge space (Colombelli, Krafft, & Quatraro, 2014; Rigby, 2015; Tanner, 2014). This implies that the similarity between the pre-existing local knowledge base and the new technological knowledge shapes knowledge recombination. 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 associated to climate change mitigation and adaptation (Montresor & Quatraro, 2020; Moreno & Ocampo-Corrales, 2022). Based on these considerations, we spell out our first working hypothesis:

H1: The relatedness between regions' existing technological capabilities and CE-related knowledge is positively correlated to the local stock of CE-related knowledge recombination

2.2. Learning dynamics and technological expertise in the green domain

Regional innovation capabilities result from localized knowledge interactions and exchange activities among local agents that trigger the accumulation of skills and knowledge (Antonelli, 1998; Freeman et al., 1987). Learning dynamics are crucial in this respect, as they influence an innovating agent's ability to combine different inputs in novel ways or discover new applications for existing combinations. Agents who have previously invested resources in accumulating tacit and codified knowledge are better equipped to manage these mechanisms. The accumulation of knowledge enhances agents' absorptive capacity, which refers to their ability to comprehend, process, and integrate external knowledge inputs (Cohen & Levinthal, 1990; Pavitt, 1988). The evolutionary process of developing absorptive capacity leads to the emergence of innovation routines, i.e., essentially established processes that support and guide innovative endeavors (Nelson, 1985). These routines involve generating new combinations and selecting the most promising research directions (Tidd & Bessant, 2018).

Learning dynamics are not only cumulative but also localized (Dosi & Grazzi, 2006, 2010). This implies that search processes and the development of new technologies tend to occur within the proximity of the technological competencies that innovating agents have already developed (Antonelli, 1995; David, 1975; Laursen, 2012; Rosenkopf & Nerkar, 2001). Consequently, while learning dynamics and the establishment of innovation routines improve the overall effectiveness of the innovation process, they also limit the scope for experimenting with new combinations due to the influence of path-dependence. In sum, the localness and cumulativeness of learning dynamics introduce both path- and place-dependent processes based on technological capabilities accumulated in local contexts to absorb and integrate new technological opportunities (Cohen & Levinthal, 1990; Colombelli et al., 2014; Henning, Stam, & Wenting, 2013; Martin & Sunley, 2006; Storper, 2018).

The characteristics of learning dynamics also affect the emergence of green technological capabilities. Recent literature has indeed 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) stressed the instrumental role of environmental innovation (EI) in achieving the CE objectives. More recently, microeconomic evidence has shown that CE solutions depend more on existing technologies that address systemic innovations rather than radical ones. Moreover, a firm's technological capabilities and knowledge sourcing from diverse networks have proven essential in fostering the production of circular eco-innovation and creating a competitive advantage (Demirel & Danisman, 2019; Kiefer, del Río, & Carrillo-Hermosilla, 2021; Triguero, Cuerva, & Saez-Martínez, 2022).

In this direction, established capabilities in green technological change can be a source of competitive advantage in CE-based recombinations, given 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, Marzucchi, & Rizzo, 2021; De Marchi, 2012; Fusillo, 2023; Fusillo, Quatraro, & Usai, 2022; Messeni Petruzzelli, Dangelico, et al., 2011). Based on these arguments, we can spell out the following hypothesis:

H2: Previous experience in the generation of GTs is positively associated to the ability to integrate and exploit new recombination opportunities in the CE field.

2.3. The role of digital complementarities

The local availability of complementary technological capabilities can play a key role in the development of regions' technological strategies. Balland and Boschma (2021a), for example, show that access to technological complementarities allows regions to escape lock-ins. Moreover, they provide evidence of the impact of technological complementarities on regional diversification patterns. Barbieri et al. (2021) shows that the development of GTs is influenced by innovation dynamics in non-green but complementary technological areas.

Digital technologies have been proposed as essential enablers of CE innovation dynamics (Bag et al., 2020; Chauhan, Parida, & Dhir, 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 in managing the increasing amount of knowledge and information flows captured and transferred among companies, tracking products and materials, and improving production and distribution processes (Salvador et al., 2021).

Following Pagoropoulos, Pigosso, and McAloone (2017) we can classify digital technologies into three categories: data collection, data integration, and data analysis. Data collection technologies encompass 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 essential for identifying inefficiencies in current business models and production methods, enabling optimization of the production process and management of the value chain (Ranta et al., 2021). Data integration and analysis technologies (e.g., AI tools, Big Data analytics) process large volumes of data to provide valuable information. These technologies are thus central in driving the adoption of innovative 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 owners about items' location and maintenance status. This facilitates access for multiple users and enables data-driven improvements in durability, preventing premature breakdowns and reducing resource consumption. In sum, digitalized systems find increasing applications in production, organization, and waste management, critical aspects of CE transition goals (Sarc et al., 2019).

Because of their enabling role and broad applicability across domains, digital technologies and AI are assimilated to General Purpose Technology (GPT) (Trajtenberg, 2019). GPTs 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 AI in particular, has also been found to increase the likelihood of regional technological diversification in the green domain (Montresor & Quatraro, 2020). However, AI seems to favor regions already possessing sound green technological specializations (Cicerone et al., 2022).

These considerations suggest that the transition to a CE could greatly benefit from digital technologies' potential to integrate multiple and technologically dispersed knowledge bits. Accordingly, the localized endowment of digital technologies can be seen as promising levers for recombinant dynamics based on CE-related technologies. Yet, the wide spectrum of digital technologies may reveal high differences in how they connect knowledge bases and favor successful recombination (Martinelli, Mina, & Moggi, 2021). Circular strategies rely on timely and effective data management and sharing, optimizing energy and material usage in both the production and utilization phases, and managing 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. On the basis of these arguments, we can spell out the following hypothesis:

H3.a: Localized cumulated knowledge in digital complementary technologies is positively associated to regional recombinant capabilities around CE-related knowledge.

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, Yan, & Rigby, 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, Boschma, & Lengyel, 2019; Miguelez & Moreno, 2018; Neffke et al., 2018; Zhu, He, & Zhou, 2017).

Within the European landscape, Santoalha and Boschma (2021) point to the role of the local development of supporting institutions in mitigating the constraining effects of relatedness on regional technological diversification in the green domain, while Perruchas, Consoli, and Barbieri (2020) shows that the impact of relatedness differs for developed vis-á-vis lagging behind regions. 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 mitigate lock-in effects triggered by related paths, enabling regions to overcome the stickiness of local capabilities.

In this direction, Montresor and Quatraro (2020) provide evidence of how the local availability of technological capabilities related to key enabling technologies (KETs) reduces the impact of relatedness in technological diversification in the green domain. On similar grounds, Santoalha et al. (2021) stresses the relevance of the availability of digital skills in local labor markets. 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. On these premises, we spell out the following hypothesis:

H3.b: Localized cumulated knowledge in digital complementary technologies negatively moderates the impact of relatedness on regional CE recombinant dynamics.

3. Data and Methodology

3.1. Identifying Circular Economy-related technologies

In order to investigate the knowledge recombination dynamics of CE technologies, we make use of patent data. Patents are commonly employed as proxies for inventions to assess technological progress since they provide granular information on the location, time, and specific technological classification of the invention. Notwithstanding the well-known drawbacks in using patent data (Griliches, 1998), primarily due to the existence of alternative protecting tools and to the different patenting rates or the impossibility to protect all inventions with patents, this remains one of the most effective ways to explore the broad set of invention activities and the recombinant pattern of CE knowledge (Jaffe & Trajtenberg, 2002; Strumsky, Lobo, & Van der Leeuw, 2012).

Data related to patents are sourced from the Organisation for Economic Co-operation and Development (OECD) REGPAT database, March 2020. We focus on patent applications at the European Patent Office (EPO) published between 1980 and 2015. We use the inventor's address, provided at the NUTS2 regional level, to detect the patents' geographic origin. [1] We also exploit the OECD Citation Database, March 2020, to retrieve all the citations in the EPO and PCT patent documents. In the case of co-invented patents with inventors residing in different regions, patent applications are proportionally allocated to all the co-inventing regions following a fractional counting procedure.

[1] Patent applications beyond 2015 are excluded because of the known drop in recorded applications due to the time required to complete the patent application process.

We rely on the widely accepted classification developed by the European Commission (EC) to identify patents related to the CE. Included in the set of CE indicators to monitor progress towards a circular economy on the thematic area of competitiveness and innovation, the EC provides a list of CPC (Cooperative Patent Classification) technological classes associated to CE.[2] The list encompasses all technological fields in the subclass Y02W: "Climate change mitigation technologies related to wastewater treatment or waste management". Accordingly, we identify as CE-related those patents classified with least one of these technology fields. In line with Cainelli et al. (2020), we focus on the development of innovative techniques for the collection, reduction, and recycling of waste, water, and materials that will help to reduce the dependence on critical commodities while improving economic resilience. The procedure allowed us to identify 6,407 CE-related patents spanning years of application from 1980 to 2015, including at least one European region among their contributors.

3.2. Empirical Strategy

The dependent variable in our empirical exercise is a measure of the region-level stock of CE-related knowledge recombination arising from patents classified as *circular*. Considering the purpose of our analysis and the limited number of CE patents by region, we count the number of patents citing at least one circular patent in the backward citations of a region's patenting portfolio.[3] Since count variables may suffer from year-to-year fluctuations in the number of patents, using stock variables allows to overcome the volatility problem, allowing to account for the cumulated knowledge, and provide a deeper insight into the phenomenon at stake. The stock of circular recombinations (*CE Stock*) is computed using the perpetual inventory method (PIM). Precisely, we calculate the cumulative stock of CE citing patents by region, applying a yearly rate of obsolescence of 15%.[4]

Our baseline specification focuses on the role of overall localized knowledge, ex-

[2] `https://ec.europa.eu/eurostat/web/circular-economy/indicators/monitoring-framework`

[3] NUTS-2 regions, being larger than NUTS-3 regions, may include a number of smaller administrative units with possible heterogeneous characteristics. Despite this limitation, two main reasons motivate our choice of considering NUTS-2 as the appropriate geographical level. Firstly, we rely on the extensive economic geography literature investigating local recombination dynamics and technological capabilities of NUTS-2 regions. The second reason is grounded on data and methodological constraints. As discussed in the previous section, CE, as well as its codified technological development, is a relatively recent construct with highly heterogenous efforts both in time and across European regions. This is confirmed by the still relatively low number of patents by NUTS-2 regions recombining CE knowledge. Measuring CE patent dynamics at the NUTS-3 levels, thus, would lead to the observation of an excessive number of regions with zero (or a few) CE citing patents in each period of our sample, thereby hindering the proper measurement of the mechanisms at stake.

[4] Existing literature made several attempts to estimate the patent depreciation rate with inconclusive 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, Jaffe, & Trajtenberg, 2005; Keller, 2002; McGahan & Silverman, 2006; Nesta, 2008).

pressed in the following form:

$$\begin{aligned} CEStock_{rt} = \alpha + \beta_1 KStock_{rt-1} + \beta_2 CErel_{rt-1} \\ + \beta_3 GDPpc_{rt-1} + \mu_{rt} \end{aligned} \tag{1}$$

where r denotes the region and t the time period consisting of 5-year time intervals from 1980 to 2015. In this first specification, the ability to recombine CE technologies is associated to the regional knowledge stock (*K Stock*) that accounts for the region's absorptive capacity and a measure of CE technological relatedness (*CE relatedness*) to capture the cognitive proximity between regions' existing technological capabilities and CE-related knowledge. The former is computed by applying the PIM method to regions' patent portfolios. In order to measure the relatedness around CE technologies, we first exploit the co-occurrence of 4-digits CPC classes in patent documents to calculate the degree of proximity between each technology s and c at time (ϕ_{sct}). Proximity is here defined as the minimum pairwise conditional probability of a region having a specialization in technology s given that it has a Revealed Technology Advantage 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 a technological specialization. Lastly, we filter the technology-specific relatedness by selecting the density value of the CE technology in order to obtain a measure of the region r relatedness around CE-related knowledge. We expect regions with a more extensive knowledge base and a higher density of the proximity linkages between CE technology and existing regional capabilities to be more likely to master CE knowledge and exploit the new technological domain for successful recombinations. We add gross domestic product (GDP) per capita (*GDP per capita*) as a control to account for the level of economic development in a region.[5] μ_{rt} is an idiosyncratic error term.

In a second specification, we investigate whether cumulated know-how in the green and digital fields may be associated to the region's circular technological recombinations. To account for the localized endowment of green-related technological knowledge, we measure, for each region, the stock of patents with a backward citation toward green patents (*GT Stock*). The identification of green-tech patents is performed according to the OECD ENV-TECH classification (Haščič & Migotto, 2015), which provides a list of technological classification codes associated to environment-related technologies based on the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).[6]

[5] GPD and population data are extracted from Eurostat.

[6] For the sake of consistency between technological classification, IPC codes are converted into CPC codes by exploiting the concordance tables available at `https://www.cooperativepatentclassification.org/cpcConcordances`

In order to identify the digital patents, we employ the classification proposed by Schmoch (2008, updated 2011). Accordingly, digital patents are those including at least one technology code that is covered by the electrical engineering area. To capture the role of regional complementary digital capabilities, we compute the stock of digital citing patents for each region, weighted by the degree of complementarity of the corresponding digital technology (*DG compl Stock*). Indeed, as mentioned in Section 2, we expect the enabling role of digital technologies in the recombination of CE knowledge to be proportional to the extent of complementarity between the digital and the CE technology fields. To operationalize this concept, for each digital technology, we calculate its degree of complementarity with respect to circular technologies. We first identify all patents co-classified in both CE and digital technologies. Then, for each digital technology, we compute the relative frequency with which it co-occurs in the hybrid CE-digital patents as a proxy of complementarity. This implies that the degree of complementarity of digital technologies is thus proportional to the extent to which they are successfully exploited in circular-related recombination. A list of the top 10 digital complementary technologies is provided in 1

Table 1. Top 10 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

The *GT Stock* and *DG compl Stock* add to equation 1, yielding the following model:

$$\begin{aligned} CEStock_{rt} = \alpha + \beta_1 GTStock_{rt-1} + \beta_2 DGcomplStock_{rt-1} \\ + \beta_3 CErel_{rt-1} + \beta_4 GDPpc_{rt-1} + \mu_{rt} \end{aligned} \tag{2}$$

Lastly, we investigate the moderating role of complementary digital knowledge on CE-specific relatedness in affecting regional CE technological recombinations. To do so, we extend the model (2) by including an interaction term between the *DG compl*

Stock and (*CE rel*), as follows:

$$\begin{aligned} CEStock_{rt} &= \alpha + \beta_1 GTStock_{rt-1} + \beta_2 DGStock_{rt-1} \\ &+ \beta_3 CErel_{rt-1} + \beta_4 DGcomplStock * CErel_{r,t-1} \\ &+ \beta_5 GDPpc_{rt} + \mu_{rt} \end{aligned} \tag{3}$$

In the models in equations 1 - 3, there could be unobserved regional characteristics not captured by our models, that may affect the regional ability to recombine CE-related knowledge. These unobserved characteristics may also be correlated with the explanatory variable. Furthermore, there may be macroeconomic shocks and technology fluctuations common to all regions in our sample that may affect regional CE recombinant capabilities. In order to control for region and period unobserved heterogeneity, we allow the error term (μ_{rt}) to include a full set of region (D_r) and time (D_t) dummies:

$$\mu_{rt} = D_r + D_t + \epsilon_{rt} \tag{4}$$

In turn, we employ two-way panel fixed-effects models estimated through OLS.[7] In all specifications, we apply the natural logarithm transformation to adjust for the skewed distribution of the continuous variables, and we cluster the standard errors on NUTS2 regions to account for heteroskedasticity.

Despite the inclusion of fixed effects and controls, the relationship between CE-based recombinations and cumulated local capabilities may raise an endogeneity issue. This may happen because successful CE-based recombination might provide incentives to regions to invest more resources in R&D and consequently in engaging in recombinant activities that increase the stock of cumulated knowledge. Further, because of the presence of technology spillovers, higher recombinant activity in green and digital complementary technologies may be the result, rather than the effect, of higher CE recombinations. At the same time, previous literature has highlighted that the use of patent stock measures might alleviate endogeneity in the analysis. Also, under the assumption that the persistence of knowledge stocks' series makes them less likely to adjust quickly to shocks, the magnitude of the potential bias associated with lagged stock series should be small in samples covering long time periods. Accordingly, in all our specifications, independent variables are lagged by one period. In addition, to further reduce biases due to potential endogeneity, the stock-based

[7]In order to check the robustness of our findings to a different estimation procedure, we use the dynamic approach of a generalized method of moments (GMM) model and implemented the GMM estimator as proposed by Arellano and Bond (1991). In particular, we employ a GMM System estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) which instruments the levels variables with lagged first differenced terms. The results of the GMM system estimator, available upon request from the authors, are qualitatively robust and confirm our main findings.

independent variables are calculated by excluding CE-related patents.

Summary statistics of the variables employed in the models are reported in Table 2. Figure 1 and 2 offer a graphical visualization of the geographic distribution over NUTS2 regions of, respectively, the stock of CE-based recombinations and the stock of digital complementary technologies, in 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.

Table 2. Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
K Stock	1,763	2,112.8590	4,662.0510	0.1250	59,095.3400
CE Stock	1,763	23.8790	44.1263	0.0000	440.1709
GT Stock	1,763	297.9278	735.0063	0.0000	10,146.9600
DG Stock	1,763	656.8777	1,805.2360	0.0000	24,008.2400
DG compl Stock	1,763	21.8665	60.1338	0.0000	812.5498
DG non-compl Stock	1,763	635.0112	1,746.9140	0.0000	23,195.6900
CE rel	1,763	0.1600	0.1202	0.0000	0.4620
GDPpc	1,685	18,466.7700	14,665.5200	452.8554	223,603.0000

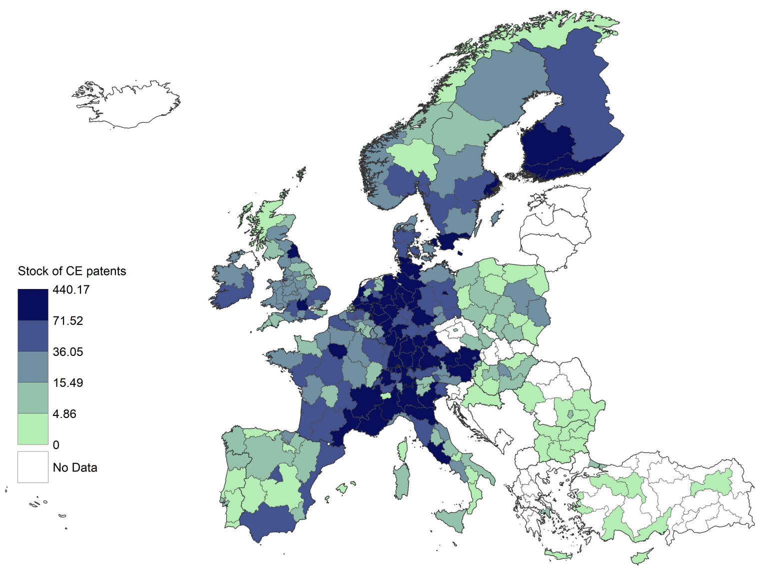

Figure 1. Geographic distribution of the stock of CE recombinations of European NUTS2 regions, from 1980 to 2015.

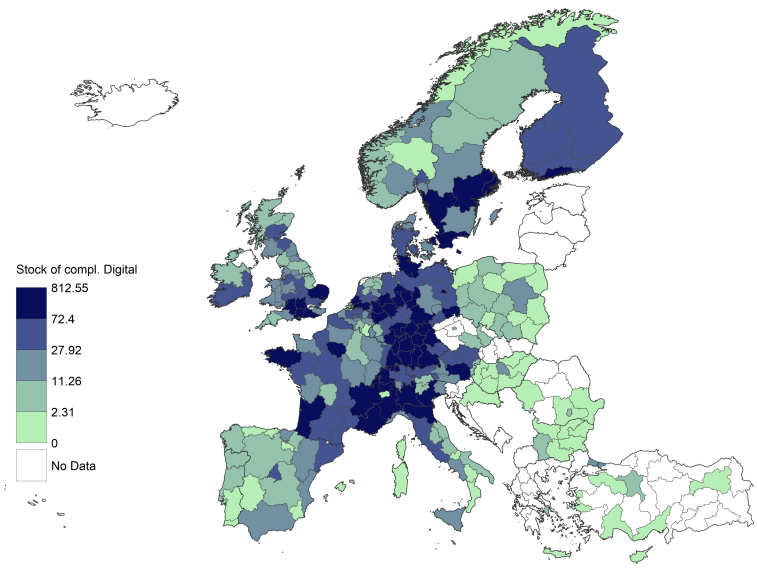

Figure 2. Geographic distribution of the stock of digital complementary technologies of European NUTS2 regions, from 1980 to 2015

4. Results and Discussion

Tables from 3 to 7 present the results of our econometric estimations.[8] Column 1 of Table 3 includes *K Stock* and *CE rel* as focal regressors. The coefficient of *K Stock* is positively and significantly associated to the ability to recombine circular knowledge. This result suggests that regional knowledge competences and absorptive capacity may facilitate the recombination process of pre-existing CE-related technologies leading to the development of new knowledge. In support of our first hypothesis H1, *CE rel* shows a positive and statistically significant coefficient in all model specifications confirming that technological capabilities in domains related to the CE might positively contribute to the circular knowledge recombination.

The model in column 2 focuses on the pre-existing green and digital expertise, including among the regressors the variables *GT Stock* and *DG compl Stock*. The cumulated know-how in both the green field and complementary digital technologies is positively associated with regions' ability to introduce new technologies stemming from the recombination of the CE knowledge. Supporting our hypotheses H2 and H3.a, these findings suggest that accumulated competencies in the green and digital sectors significantly contribute to circular knowledge recombination and creation. This also highlights that the knowledge developed within the two fields that characterize the "twin transition" may be assimilated and exploited in knowledge generated through the recombination of circular competencies.

[8]Results' table report at the bottom the mean value of the VIF tests performed across all specifications. The mean value and the individual VIF values of all the variables below 10 – the upper bound generally indicated by the relevant literature – allow us to exclude critical multicollinearity issues.

In model 3, we add the interaction term *DG compl Stock * CE rel* to investigate if and to what extent the complementarity between digital and circular technologies might moderate the role of CE relatedness on CE recombinant activity. The estimated coefficient is negative and significant, suggesting that complementary digital capabilities seem to attenuate the role of CE-relatedness. Overall, increasing innovation through the recombination of pre-existing CE knowledge is facilitated by technological similarity with the extant knowledge base. However, it appears that established competencies in digital fields – complementary to the circular one – help regions to advance their knowledge as a result of the recombination of CE know-how, possibly making the acquisition of new technological solutions more accessible to regions with knowledge bases less cognitively close to the circular one. In line with our hypothesis H3.b, digital complementary knowledge may not only contributes directly to the development of new technological knowledge but also shrink the risk of lock-ins due to relatedness.

Interestingly, our findings suggest that it may not be digital technology per se that is conducive to recombination, but rather its complementarity with CE technologies. Accordingly, we re-estimate models 2 and 3 considering, alternatively, the total stock of digital technologies or the stocks of complementary and non-complementary digital technologies. Results, presented in Table 4, show a positive estimated coefficient for the digital knowledge stock, though modest in magnitude and statistical significance. In models 2 and 3, we detect a non-significant role of the stock of non-complementary digital technologies. At the same time, the coefficient of *DG compl Stock* is still positive and highly significant. Results hold when introducing the interaction term *DG compl Stock * CE rel*, which shows, as expected, a negative and significant estimated coefficient.

To deeply delve into the relation between technology-specific regional knowledge stocks and knowledge advancement through circular recombination processes, we explore whether different green and digital technological sub-fields play a role. To this end, we run an additional set of regressions, replacing the knowledge stock explanatory variables, with the stocks calculated for each green and digital technological sub-field. Based on the ENV-TECH classification (Haščič & Migotto, 2015), we differentiate green technologies between two macro-technology groups: adaptation technologies and mitigation technologies. [9] Following Schmoch (2008, updated 2011), digital technologies are broken down into: electrical machinery, apparatus, energy; audio-

[9] The former encompasses (a) environmental management and (b) water-related adaptation technologies; the latter includes (c) climate change mitigation technologies (CCMT) related to energy generation, transmission or distribution, (d) capture, storage, sequestration or disposal of greenhouse gases, (e) CCMT related to transportation, (f) CCMT related to buildings, (g) CCMT related to wastewater treatment or waste management, and (h) CCMT in the production or processing of goods.

visual technology; Telecommunications; digital communication; basic communication processes; computer technology; IT methods for management; semiconductors.

Tables from 5 to 7 report the results. Starting with the green sub-fields, Table 5 shows a positive association with both adaptation and mitigation technologies. Indeed, the former category includes environmental management-related technologies, among which installations for pollution and emissions abatement, and the collection and processing of a wide range of discarded materials. The second category encompasses technologies seeking to limit the emissions of greenhouse gases with particular reference to the energy and transport sector, buildings construction, and the production and processing of goods. Most of these are specifically designed for the recovery and recycling of materials, such as the reuse of by-products or heat recovery, the energy efficiency of the production processes, and the energy production from renewables. Hence, it is not surprising that technologies for the substitution of non-renewable and scarce resources for renewable ones both in manufacturing and in energy generation might be more easily integrated into the recombination of circular knowledge.

Moving to the disaggregated analysis of the digital knowledge stocks, as reported in Tables 6 and 7, we found a statistically significant role of the digital complementary IT methods, digital communication, computer technology, and electrical machinery technology fields in facilitating the CE knowledge recombination dynamics (Table 6) and in moderating the role of the CE relatedness (as shown in Table 7). The computer technology sub-field comprises technologies related to image and speech recognition and processing, digital or analogue information storage, and information and communication technology (ICT) adapted for specific purposes. ICT, in particular, is crucial in facilitating end-of-use strategies and collaborative consumption models. Indeed, these technologies allow for remote monitoring, which helps companies to reveal inefficiencies in their processes and detect failures in their products or users' activity. Similarly, data collected from the logistics system may be used to optimize the logistic operations, including the take-back in the supply chain. ICT adapted for the Internet of Things (IoT), enabling physical objects to sense and collect information from their internal state or external environment, can also enhance waste management systems. Further, in a user-oriented PSS where products are equipped with IoT sensors, it becomes possible to track their location and monitor the condition and availability of the products themselves, as all the items are connected to a platform and virtually communicate via software.

The sub-class IT methods consists of technologies to deal with complex data processing operations, while digital communication technologies cover the transmission of signals in digital form and wireless communication systems. Our results, thus, confirm the role that systems for data processing and the transmission of digital information may play in integrating CE-related knowledge. Indeed, many circular strategies rely on timely and effective data management and sharing, e.g.: the optimization of energy and material usage, the management of forward and reverse logistics, products, and assets sharing.

Lastly, complementary electrical machinery technologies cover various generators, engines, and other electric elements. Though positive, their role seems to be less pronounced compared to the other digital subfields, in line with recent studies suggesting that the circular transition tends to be less driven by incremental improvements of physical machinery, requiring instead the innovative rethinking of production and consumption systems.

Table 3. CE recombinations, localized knowledge and digital complementarities

	(1)	(2)	(3)
K Stock	0.1669***		
	(0.0472)		
GT Stock		0.2027***	0.1680***
		(0.0438)	(0.0452)
DG compl Stock		0.1468***	0.3202***
		(0.0406)	(0.0669)
CE rel	3.9507***	2.9141***	3.3805***
	(0.4861)	(0.4624)	(0.4894)
DG compl Stock * CE rel			−0.4877***
			(0.1607)
GDPpc	0.1353*	0.2793***	0.2564***
	(0.0780)	(0.0768)	(0.0748)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
mean VIF	4.25	4.232	5.384
Observations	1,345	1,345	1,345
R^2	0.2061	0.2517	0.2636
F Statistic	94.7300***	91.9966***	78.2411***

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

Table 4. CE recombinations, localized knowledge, complementary and non complementary digital technologies

	(1)	(2)	(3)
GT Stock	0.1900***	0.1816***	0.1675***
	(0.0510)	(0.0483)	(0.0484)
DG Stock	0.0745*		
	(0.0398)		
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	2.9842***	2.7995***	3.3751***
	(0.4886)	(0.4560)	(0.5044)
DG compl Stock * CE rel			−0.4858***
			(0.1740)
GDPpc	0.1767**	0.2632***	0.2560***
	(0.0744)	(0.0806)	(0.0783)
Time FE	YES	YES	YES
NUTS2 FE	YES	YES	YES
mean VIF	4.816	4.982	6.113
Observations	1,345	1,345	1,345
R^2	0.2373	0.2532	0.2636
F Statistic	85.1099***	74.1274***	65.1417***

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

Table 5. CE recombinations, localized knowledge and digital complementarities (green-tech fields)

	(1)	(2)	(3)	(4)
GT Adapt Stock	0.2054***	0.1857***		
	(0.0408)	(0.0402)		
GT Mitig Stock			0.1914***	0.1702***
			(0.0383)	(0.0375)
DG compl Stock	0.1109***	0.3080***	0.0998**	0.2918***
	(0.0414)	(0.0652)	(0.0444)	(0.0670)
CE rel	3.0836***	3.4756***	3.1741***	3.5604***
	(0.4377)	(0.4415)	(0.4532)	(0.4595)
DG compl Stock * CE rel		−0.5542***		−0.5329***
		(0.1515)		(0.1511)
GDPpc	0.3189***	0.2868***	0.3098***	0.2796***
	(0.0767)	(0.0748)	(0.0741)	(0.0723)
Time FE	YES	YES	YES	YES
NUTS2 FE	YES	YES	YES	YES
mean VIF	4.124	5.176	4.106	5.183
Observations	1,345	1,345	1,345	1,345
R^2	0.2573	0.2735	0.2576	0.2725
F Statistic	94.7338***	82.2954***	94.9197***	81.8830***

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

Table 6. CE recombinations, localized knowledge and digital complementarities (main digital fields)

	(1)	(2)	(3)	(4)
GT Stock	0.2151***	0.2121***	0.2180***	0.2147***
	(0.0432)	(0.0444)	(0.0445)	(0.0433)
Computer Tech Stock	0.1341***			
	(0.0353)			
DG communications Stock		0.1190***		
		(0.0337)		
Electrical Machinery Stock			0.0910**	
			(0.0407)	
IT methods				0.1272***
				(0.0332)
CE rel	3.5678***	3.7673***	3.0841***	3.6298***
	(0.4819)	(0.5322)	(0.4800)	(0.4912)
GDP per capita	0.2723***	0.2473***	0.2523***	0.2673***
	(0.0749)	(0.0731)	(0.0782)	(0.0750)
Time FE	YES	YES	YES	YES
NUTS2 FE	YES	YES	YES	YES
mean VIF	3.823	3.725	4.122	3.7459
Observations	1,345	1,345	1,345	1,345
R^2	0.2534	0.2486	0.2404	0.2544
F Statistic	92.8125***	90.4988***	86.5630***	93.3124***

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

Table 7. CE recombinations, localized knowledge and digital complementarities (main digital fields)

	(1)	(2)	(3)	(4)
GT Stock	0.1971***	0.2045***	0.1914***	0.1993***
	(0.0427)	(0.0440)	(0.0454)	(0.0427)
Computer Tech Stock	0.4909***			
	(0.0913)			
DG communications Stock		0.4063***		
		(0.0896)		
Electrical Machinery Stock			0.2618***	
			(0.0744)	
IT methods				0.4923***
				(0.0947)
CE rel	3.9789***	3.8980***	3.5095***	3.9114***
	(0.4752)	(0.5251)	(0.4993)	(0.4788)
Computer Tech Stock * CE rel	−1.1098***			
	(0.2637)			
DG communications Stock * CE rel		−0.9609***		
		(0.2773)		
Electrical Machinery Stock * CE rel			−0.4977***	
			(0.1812)	
IT methods Stock * CE rel				−1.1699***
				(0.2769)
GDP per capita	0.2585***	0.2292***	0.2399***	0.2458***
	(0.0731)	(0.0725)	(0.0763)	(0.0727)
Time FE	YES	YES	YES	YES
NUTS2 FE	YES	YES	YES	YES
mean VIF	5.268	5.019	5.368	5.024
Observations	1,345	1,345	1,345	1,345
R^2	0.2727	0.2576	0.2499	0.2751
F Statistic	81.9470***	75.8338***	72.8372***	82.9792***

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

5. Conclusions

According to the widely recognized recombinant knowledge framework, the innovation process leading to the production of new knowledge relies on the recombination of the existing wealth of knowledge. Regions are expected to leverage on the technological capabilities cumulated at the local level to advance their knowledge. Building on this strand of research, this paper investigates the role of region- and technology-specific cumulated knowledge on the recombination of localized knowledge CE field. The increasing interest in the CE has led governments and industries to adopt policies and strategies to overcome the linear economic model. Yet, the literature on innovation and regional economics has given little attention to the innovative processes that generate circular knowledge and that stem from it. More precisely, a gap still exists in our knowledge of the drivers that could foster the recombinant dynamics around circular technologies and lead to the development of further knowledge.

We address this gap by exploiting a sample of European NUTS-2 regions over the period 1980-2015 and patent data as a proxy of technological invention. Our analysis provides novel empirical evidence on the relationship between pre-existing regional knowledge competencies, and the relatedness between CE technology and local knowledge bases, which may facilitate the successful recombination of CE-related knowledge for new knowledge creation. We show that the localized stock of green and digital knowledge – complementary to the circular one – may ease regional recombination processes of CE-related technologies. In particular, our findings suggest that the know-how at the heart of the envisaged twin transition may represent a crucial factor in fostering circular knowledge recombination dynamics. We further provide a more accurate picture of the role of the green and digital technological cumulated capabilities in specific sub-domains. Notably, both green adaptation technologies and CCMT seem to play a central role, while, among the complementary digital technologies, IT methods, digital communication, computer technology are associated to successful CE-based recombination to a greater extent with respect to improvements in physical machinery (electrical machinery technologies).

Our study is not free from caveats. The first limitation is related to the use of patents to proxy for technological efforts and to the classification of CE-related technologies provided by the EC, mostly focused on wastewater treatment and waste management, which are crucial but partial features of the CE. Secondly, despite the increasing concerns about the need to understand innovation processes for a sustainable CE transition, focusing on the technologies related to the CE may come at the risk of underestimating the wide range of CE practices introduction and adoption. Nevertheless, extant literature highlighted that while CE innovation is still relatively incremental, the innovative efforts in searching for radical solutions and achieve a full

CE transition show an increasing technological reliance, based on the larger potential of technology advancement and their recombination opportunities. Similarly, given the systemic nature of digitalization, patent data might not capture the full spectrum of digital technologies and their impact on production and innovation processes, despite their increasingly codified content, providing only a partial account of the digital enabling role. Third, notwithstanding the methodological precautions introduced, our empirical exercise does not allow us to rule out potential endogeneity concerns, and further studies may be required to claim the existence of causal relationships in our findings.

In spite of these limitations, this work contributes to the previous literature and public debate in two ways. First, we shed new light on the mechanisms behind the generation of new knowledge by means of the recombination of circular technology, highlighting the crucial role of local cumulated knowledge capabilities at the regional level. Second, we make a step forward in the consideration of regional recombinant dynamics, showing that, on the one hand, green-digital local capabilities are essential to trigger continuous knowledge improvements and the necessary transition to low-impact economies; on the other hand, that the enabling role of digital technologies in integrating multiple and technologically dispersed knowledge bits is more effective in regions endowed with digital capabilities complementary to the circular technology domain.

These contributions also bear important policy implications. Directing regional innovative activities toward green and digital technologies through policy actions aimed at prioritizing the reinforcement of local existing capabilities could be a leverage for the elaboration of successful strategies to promote research and innovation in the CE-related domain and the successful integration of new circular knowledge. Indeed, limited awareness of the benefits, opportunities, and complexities associated with the importance of local cumulated capabilities might have limited the incentive and resources deployed in developing strategic policies. Relatedly, regional policy-makers might face regulatory or institutional barriers and competing priorities, which may hinder the integration of CE, digital, and green technologies. Thus, strengthening the institutional framework and providing incentives for the successful transfer of technological capabilities acquired in green and digital complementary fields might be more effective in supporting regional recombinant capabilities. Lastly, recognizing the relevance of the exploitation of digital technological complementarities calls for policy efforts aimed at fostering the identification and development of such digital complementary capabilities. This suggests the need to exploit knowledge hybridization, complementarities, and spillover between CE and digital technologies domains by designing strategic policies that support the creation of network dynamics among inventors, firms, universities, and regional actors, boosting the integration of their different skills and competences. Yet, because of fragmented governance structures, regional policy-makers may struggle to deploy collaborative ecosystem policies, whose effective implementation requires resources and coordination across multiple governance levels.

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