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Regional Studies

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/cres20

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To cite this article: Carlo Corradini & Michail Karoglou (2022): On the persistence and complementarities of design and technological change: a regional perspective, Regional Studies, DOI: 10.1080/00343404.2022.2120975

To link to this article: https://doi.org/10.1080/00343404.2022.2120975

REGIONAL STUDIES
https://doi.org/10.1080/00343404.2022.2120975

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On the persistence and complementarities of design and technological change: a regional perspective

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ABSTRACT
This paper explores the dynamics between design and technological change for regional innovation. We discuss a framework integrating persistence effects and processes of knowledge recombination that explicitly recognize the role of design as a separated yet synergic element to technological change within the context of regional innovation systems. Using a panel vector autoregressive (PVAR) approach and information on over 900 NUTS-3 regions across 20 countries in Europe for the period 2000–12, we provide novel evidence of evolutionary dynamics for both design and technological change along with simultaneous complementarities expanding the set of combinatorial opportunities for regional innovation.

KEYWORDS
patents; design; trademarks; persistent innovation; knowledge bases; evolutionary economic geography

JEL C33, O33, R11, R12
HISTORY Received 5 November 2020; in revised form 16 July 2022

1. INTRODUCTION

One of the striking features defining the geography of innovation is the marked and persistent heterogeneity in knowledge production across regions (Breschi, 2000; Malecki, 2010). Differences in innovation across regions have long been conceptualized as a function of the uneven distribution of formal and informal knowledge endowments and the presence of inter-firm interactions and connections across traded and untraded interdependencies that define regional combinative capabilities and collective learning (Boschma, 2005; Camagni, 1991). In line with the insights offered by endogenous growth theory (Aghion & Howitt, 1998; Romer, 1990), and research in evolutionary economic geography (Boschma & Frenken, 2006; Boschma & Martin, 2010), scholars have emphasized the localized and place-specific nature of knowledge flows in defining cumulative knowledge capabilities underpinning increasing returns in innovation.

Building on this, a large strand of research has explored innovation as a process of recombination shaped by the place specific structure of the technological knowledge space (Castaldi et al., 2015; Corradini & De Propris, 2015; Miguelez & Moreno, 2018). Likewise, evolutionary perspectives have applied this recombinant hypothesis framework to underline the path-dependent and persistent nature of regional technological trajectories (Boschma & Martin, 2010; Kogler et al., 2017). These studies have demonstrated the importance of combinations of related and unrelated knowledge for the creation of innovation. Conversely, evidence on endogenous learning effects reflecting true state dependence in technological change has received less attention at the regional level.

Furthermore, quantitative research on combinative opportunities and place-specific dynamics of innovation has mostly focused on the analysis of technological change (Stoneman, 2010). Whilst this has led to critical insights, it does not fully reflect the multidimensional nature of innovation activities (Malecki, 2010). Scholars have long underlined a fundamental distinction between functional and aesthetic – or symbolic – dimensions (Hirschman, 1982) of new products to emphasize the importance of design, alongside technological knowledge, as a key element within the innovation process (D'Ippolito, 2014; Utterback et al., 2006), pointing to the presence of strong interconnections and linkages combining the design function with technological change (Stoneman, 2010; Walsh, 1996). More generally, theoretical perspectives on regional systems of innovation describe processes of localized collective learning and knowledge creation as transcending

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/00343404.2022.2120975.

the dichotomy between tacit and codified knowledge (Polanyi, 1967), occurring across differentiated knowledge bases that span from analytical and synthetic to symbolic functions (Asheim et al., 2007; Asheim et al., 2011; Martin & Moodysson, 2011). Accordingly, a growing literature in the last decade has started unpacking the importance of creative industries for regional innovation (Cooke & De Propris, 2011; Lee & Drever, 2013; Lee & Rodríguez-Pose, 2014; Sleuwaegen & Boiardi, 2014). Similarly, recent contributions have explored regional diversification looking at trademark data to capture innovation across small firms and in the service sector (Block et al., 2021; Drivas, 2020).

Notwithstanding these important insights, evidence on the presence of localized evolutionary effects in design innovation and symbolic knowledge bases remains limited. More importantly, studies on different types of innovation activities and differentiated knowledge bases have remained largely separated, leading to scant discussion and empirical evidence on the potential interdependencies and co-evolutionary complementarities (Fritsch et al., 2019) between design activities and technological change for regional innovation.

In this paper, we endeavour to contribute to the literature exploring the systemic interaction of location-specific cumulative dynamics of design and technological innovation and the synergies that their interplay may create for regional innovation. Merging insights from evolutionary economic geography (Boschma & Frenken, 2006; Boschma & Martin, 2010) and the literature on learning regions and differentiated knowledge bases (Asheim et al., 2007; Asheim et al., 2011; Cooke et al., 1997), we address two questions. First, we ask if design activities are characterized by persistence effects in localized learning as patents, with current levels of innovative activity being shaped by previous successes, leading to dynamic increasing returns within regions. Second, we explore whether there are synergies and complementarities between different knowledge bases, in the form of design and technological change activities, expanding the set of combinatorial opportunities that underpin regional innovation.

To test such hypotheses, we use a longitudinal dataset for over 900 NUTS-3 regions across 20 countries in Europe for the period 2000–12 comprising information on patents as proxies of technological change and registered community designs (RCDs) as well as trademarks for design activities. The analysis is conducted using a panel vector autoregression (PVAR) approach to enable us to treat both design and technological change variables as endogenous within the system and, in turn, to test the hypothesis of persistence in innovation for both dimensions as well as the presence of a mutually causal relationship. Our results provide evidence of persistent innovation at the regional level for patents and extend findings on such dynamics to design activities. Furthermore, the paper provides novel evidence in favour of simultaneous positive effects between design and technological change, highlighting the synergies between these dimensions within regional innovation systems.

In the remainder of the paper we first review the literature and present our hypotheses. We then outline the data and the PVAR methodology employed before reporting and discussing the results in the following section. The final section concludes by reviewing our contribution alongside a set of academic and policy implications.

2. LITERATURE REVIEW AND HYPOTHESES

Exploring the localized nature of learning processes and knowledge creation (Boschma, 2005), scholars have conceptualized regions as nodes of interaction and connectivity where different actors in the innovation process are linked together by commonalities and complementarities through formal and informal interdependencies rooted in specific knowledge bases, thereby defining a regional system of innovation (Asheim & Gertler, 2005; Cooke et al., 1997). The importance of geographical proximity for innovation rests upon the fundamental role of local embeddedness and interaction for the transferability and recombination of knowledge into new ideas (Boschma, 2005; Gertler, 2003; Storper & Venables, 2004). This spatially bound dimension of systemic learning processes is usually explained as being defined by the presence of tacit and uncodifiable knowledge within innovation activities (Gertler, 2003; Polanyi, 1967), the localized patterns of inventors' mobility (Breschi & Lissoni, 2009), and the contextual nature of knowledge which is shaped across place-specific norms, communities and informal institutions that constitute the relational infrastructure of regions (Capello, 2002; Storper, 2018).

Within this framework, spatial concentration of innovative activities results from the mutually reinforcing effects between the proximate nature of knowledge externalities and a strong cumulative character in the returns from innovation. The latter reflects central elements of evolutionary economics theory (Nelson & Winter, 1982), indicating technological change presents a cumulative nature following path dependent trajectories. These define dynamic increasing returns where innovation spurs innovation, further strengthened through learning by doing and learning to learn effects (Klevorick et al., 1995; Rosenberg, 1976). Such persistence effects in technological change are not confined within firms, and similar processes have been suggested in relationship with the marked heterogeneity in the distribution of innovative activity across European regions (Breschi, 2000; Soo, 2018). In particular, reflecting insights from endogenous growth theory on increasing returns from knowledge creation (Aghion & Howitt, 1998; Romer, 1990), scholars in evolutionary economic geography have indicated regions may similarly display innovation persistence dynamics (Boschma & Frenken, 2006; Boschma & Martin, 2010). As regions increase their innovative output, new knowledge created translates into a key source of novel ideas. Due to the localized nature of knowledge spillovers (Jaffe et al., 1993), this increases place-specific knowledge capabilities and learning opportunities for successive innovation activities, so that technological change is not only path dependent, but also place dependent (Martin & Sunley, 2006).

While these insights have been traditionally developed through the analysis of technological change, scholars increasingly underline the need to discuss innovation activities as being comprised of different types of knowledge defined by diverse characteristics and attributes (Malecki, 2010). In particular, the literature on differentiated knowledge bases indicates that differences across regional innovation systems may be conceptualized looking at the specific knowledge input that defines localized innovation processes (Asheim et al., 2007, 2011; Asheim & Gertler, 2005; Martin & Moodysson, 2013). Looking beyond traditional dichotomies between high-tech and low-tech sectors or tacit and codified knowledge, this stream of research focuses instead on three epistemologically distinct forms of knowledge creation. An analytical knowledge base is rooted in scientific methods and formal models, with both knowledge inputs and outputs being distinctly codified in nature. Synthetic knowledge is generated through interactive learning where knowledge creation follows an inductive rather than deductive process and it is context specific but at least partially codified. In contrast, a symbolic knowledge base reflects creative functions directed at producing new designs, symbols and images that rest upon tacit elements and interpretation rather than information processing (Asheim, 2007; Asheim et al., 2007; Martin & Moodysson, 2011). The contribution of symbolic knowledge goes beyond aesthetic features to comprise emotional values and the generation of new 'meanings' (Verganti, 2018). These categories broadly reflect insights from the economics of innovation literature juxtaposing technological invention, often identified through patents, and design as well as trademarks as being reflective of symbolic functions revealing reputational assets and 'soft' innovation in services and creative industries (Castaldi, 2018, 2020; Stoneman, 2010).

Extending the hypothesis of regional persistent innovation in design activities and symbolic knowledge ultimately resides on whether these also follow a localized and embedded nature defining spatially bound cumulative effects. Design functions tend to be far less resource-intensive than formal research and development (R&D) and technological activities, taking place in different forms across a wider sectoral variety (Walsh, 1996). This is in contrast with key stylized facts on persistent innovation, usually associated with large firm size, sectoral concentration and high barriers to technological entry that shape the cumulative dynamics internal to the firm (Corradini et al., 2016; Geroski et al., 1997). Similarly, the role of sunk costs in R&D for persistent innovation (Sutton, 1991) may also be less relevant in the case of design. However, cumulative dynamics external to the firm may exert a more important effect for design activities.

For example, firms have long used a varied share of in-house and consultant designers (Walsh, 1996), and externalization of design functions now represents an established strategy in all advanced economies (Filippetti & D'Ippolito, 2017; Utterback et al., 2006). This reflects the more systemic structure that characterizes design activities, with firms often connected in a dense network where geographic proximity is still predominant (Cooke & De Propris, 2011; Martin & Moodysson, 2011). While sources of inspiration are not confined to proximate locations, spatially bound linkages and face-to-face interaction remain fundamental for knowledge transfer among the actors involved, frequently requiring long-term strong ties and the clustering of creative industries (Lazzeretti et al., 2008; Sunley et al., 2008). Such a strong connection between places and design is defined by the embeddedness of symbolic knowledge and the contextual nature of interpretation as well as construction of new aesthetic attributes and meanings within design processes (Asheim et al., 2011; Aspers, 2009; Martin & Moodysson, 2011). Thus, we posit it is possible to extend the theoretical framework on persistent innovation to both technological change and design activities at the regional level.

Hypothesis 1a. There are dynamic increasing returns in technological change at the regional level.

Hypothesis 1b. There are dynamic increasing returns in design innovation at the regional level.

So far, the discussion has looked at the dynamics of technological change and design activities as if they were independent within regions. In contrast, the discussion on the relationship between spatial proximity and the effectiveness of interactive learning has underlined the importance of co-location of diverse technological capabilities in order for innovation to occur through variety in cognitive proximity (Boschma, 2005). A large literature underlines the role of related variety in localized capabilities in shaping processes of innovation and new path development across regions (Castaldi et al., 2015; Kogler et al., 2017; Miguelez & Moreno, 2018). At the same time, unrelated variety may reduce lock-in effects and allow for novel recombination resulting from a complex interconnection of dissimilar but complementary knowledge components (Nooteboom et al., 2007; Corradini & De Propris, 2017). Accordingly, previous studies show recombination of diversified knowledge and unrelated variety to be important elements for regional innovation and entry patterns of new technologies (Castaldi et al., 2015: Corradini & De Propris, 2015).

Whilst this strand of research has explored regional innovation looking at related and unrelated variety across technological domains, cross-fertilization of ideas and synergies are not confined only within formal processes of R&D activities focused on the development of new technologies. This is a central element in the literature on differentiated knowledge bases, where interactive learning and knowledge flows occur through localized interdependencies and distributed knowledge networks connecting engineering and science-based activities, rooted in analytical and synthetic knowledge bases, and symbolic knowledge underlying design activities (Asheim et al., 2007; Asheim et al., 2011; Martin & Moodysson, 2011). Researchers have long underlined the linkages and complementarities between design, R&D and product innovation at the firm level (Corradini & D'Ippolito, 2022; Walsh, 1996). As Jensen et al. (2007) point out, modes of innovation based on scientific knowledge benefit from linkages with informal processes of interactive learning within and between departments as well as outside the firm. At the meso-level of regional innovation systems, localized co-occurrence of differentiated knowledge bases may expand the set of combinatorial opportunities for innovation, leading to contemporaneous spillovers as the knowledge created in one spurs innovation activities in another.

Recent research (Grillitsch et al., 2017) has suggested the analytical knowledge base, connected to formal R&D and scientific activities, may have a prominent role for regional innovation; and it is certainly possible to image the introduction of a new technology leading to complementary design activities that extend the functionality of new products with novel symbolic meanings (Eisenman, 2013). Similarly, recent research has provided evidence of a positive effect of regional patenting on trademark applications (Block et al., 2021; Drivas, 2020). However, the exact opposite may also occur. Design activities represent a fundamental source of creativity within the innovative process 'where the "coupling" occurs between technical possibilities and market demands or opportunities' (Walsh, 1996, p. 514). In this sense, design can be seen as 'creative brokering' (Sunley et al., 2008), fostering the transfer and synthesis of ideas across diverse domains and nodes of localized production networks. Partial evidence for this brokering effect is offered by the research on creative occupations. Exploring the case of London, Lee and Drever (2013) find a positive relationship between such occupations and the introduction of new products in the area. Lee and Rodríguez-Pose (2014) extend these findings showing creative occupations foster the introduction of innovations learnt elsewhere. Similarly, Castaldi (2020) indicates how trademarks may reveal complementary innovation in services, low-tech manufacturing and creative industries. These activities may generate learning effects and spillovers connecting to other knowledge bases within regional innovation systems.

Accordingly, we posit the dynamic increasing returns defined by spatially bound cumulativeness in both technological change and design activities mutually reinforce each other, fostering synergies and complementarities across the different layers and functions of regional knowledge networks.

Hypothesis 2. There is a positive simultaneous effect between design and technological change activities in regional innovation.

3. DATA

The analysis is based on Eurostat data covering over 900 NUTS-3 regions[1] in over 20 European countries for the period 2000–12. In line with our research question, the primary data features we focus on are technological change and design innovation.

We capture technological change by defining the variable *PATINT* as the number of patent applications to the European Patent Office (EPO) by total population for each NUTS-3 region. The strengths and weaknesses of patents as measure of innovation are well known and are widely considered that they offer an objective measure of novelty due to the requirement of a significant inventive step; yet their application mostly reflects technology-based innovations (Archibugi & Planta, 1996; Griliches, 1990). Consequently, they are considered as an effective proxy for regional innovation and unsurprisingly have been used extensively in the literature as measure of regional technological change (Acs et al., 2002; Parent & LeSage, 2012; Soo, 2018).

In the same spirit, we measure design innovation by defining the variable *DESINT* as the summation of two related variables. The first variable, denoted as *RCDINT*, is the ratio of the number of RCD over the total regional population. The second variable, denoted as *TDMINT*, is the ratio of the number of trademarks registered at the European Union Intellectual Property Office (EUIPO) over the total population.

In particular, an RCD is a unitary industrial design right that is valid across the European Union, offering legal protection[2] on the appearance of the whole or part of a product. This includes its shape, patterns and colours as well as texture. In line with the community design regulation (EC 6/2002) defining EU-wide design rights, any industrial or handicraft item including packaging, graphic symbols and typefaces may qualify as a product.

Likewise, trademarks provide legal protection on the exclusive use of any sign, mark, words or other symbols to identify specific goods or services of one enterprise from those of other enterprises (EU Regulation 2017/1001). They have a validity of 10 years but can be renewed indefinitely. Like patents, applications for industrial design and trademark protection vary across industries, although their use is also widespread in low-tech industries (Castaldi, 2018; Filitz et al., 2015). Yet, firms are increasingly engaging with mechanisms enabling the appropriation of rents rooted in design-based innovation (Filippetti & D'Ippolito, 2017), aimed at protecting their design innovations from imitators (Gemser & Wijnberg, 2001).

Similarly to patents, both RCDs and trademarks offer an objective measure of novelty with detailed information across longitudinal and geographical dimensions (Filitz et al., 2015; Yoshioka-Kobayashi et al., 2018). Escaping approaches based on creative occupations, often not reported or correctly specified by firms, Filitz et al. (2015) suggests that RCDs may be particularly useful to explore interactions between design-related innovation and technological change. Correspondingly, trademarks are not related to technological invention; instead, they work effectively in the context of creative industries and 'soft' innovation (Castaldi, 2018; Stoneman, 2010). In this sense, their function 'matches the symbolic and conceptual nature of most non-technological innovations' (Castaldi, 2020, p. 476).

In this set-up, we start exploring similarities and differences in the spatial patterns of design and technological change by examining patterns for *PATINT* and *DESINT* across NUTS-3 regions. These are reported across five quantiles of distribution in Figure 1.

Overall, the distribution in the rates of patent and design intensity is noticeably uneven, with significant heterogeneity across but also within countries. In the case of patents, we observe the well-known concentration in the core EU regions in Germany and northern Italy, as well as the clusters around the main capital cities in Northern Europe. For design activities, the map reflects insights from the literature on creative industries, also showing uneven spatial distribution defined by linkages to highly agglomerated regions and strong clusters around larger urban areas (Boix et al., 2016; Lazzeretti et al., 2008). In contrast to patents, values for *DESINT* appear more distributed across regions, reflecting the lower R&D intensity of design innovation, with higher values across Southern and Eastern EU regions.

4. METHODOLOGY

To capture the persistence dynamics of technological change and design innovations and their interdependent relationship we apply a panel vector autoregressive (PVAR) model (Gilchrist & Himmelberg, 1995; Holtz-Eakin et al., 1988), whose structure is designed to account both for dynamic behaviour and cross-dependence of the underlying variables.

In particular, we define a general bivariate model in which *PATINT* and *DESINT* are treated as endogenous variables within a system of equations (one for each endogenous variable). Within the PVAR framework, each of these endogenous variables is explained by (1) their own lagged values; (2) the lagged values of the other endogenous variable; and (3) a set of control variables exogenous to the system. This allows us to follow the insights from evolutionary economic geography (Boschma & Frenken, 2006; Boschma & Martin, 2010), where the output of innovation in a specific point in time becomes the input for the next round of innovation, reflecting endogenous processes and potential co-evolutionary complementarities (Fritsch et al., 2019) of cumulative learning.

Following the notation of Love and Zicchino (2006) and Abrigo and Love (2015), a k-variate PVAR model of order p with panel-specific fixed effects can be described by the following system of equations:

$$Y_{it} = \sum_{k=1}^{p} Y_{it-k}A_k + X_{it}B + u_i + e_{it} \quad (1)$$

where $i \in \{1, 2, \ldots, N\}$, $t \in \{1,2, \ldots, T_i\}$, Y_{it} is a $(1 \times k)$ vector of dependent variables; X_{it} is a $(1 \times l)$ vector of exogenous covariates; and u_i and e_{it} are, respectively, $(1 \times k)$ vectors of dependent variable-specific fixed effects and idiosyncratic errors which are assumed to be uncorrelated over time and distributed around zero with constant variance–covariance matrix.[3] The $(k \times k)$ A matrices and the $(1 \times k)$ matrix B contain the parameters to be estimated.

Estimation of such a PVAR model is not straightforward. The standard mean-differencing methods to

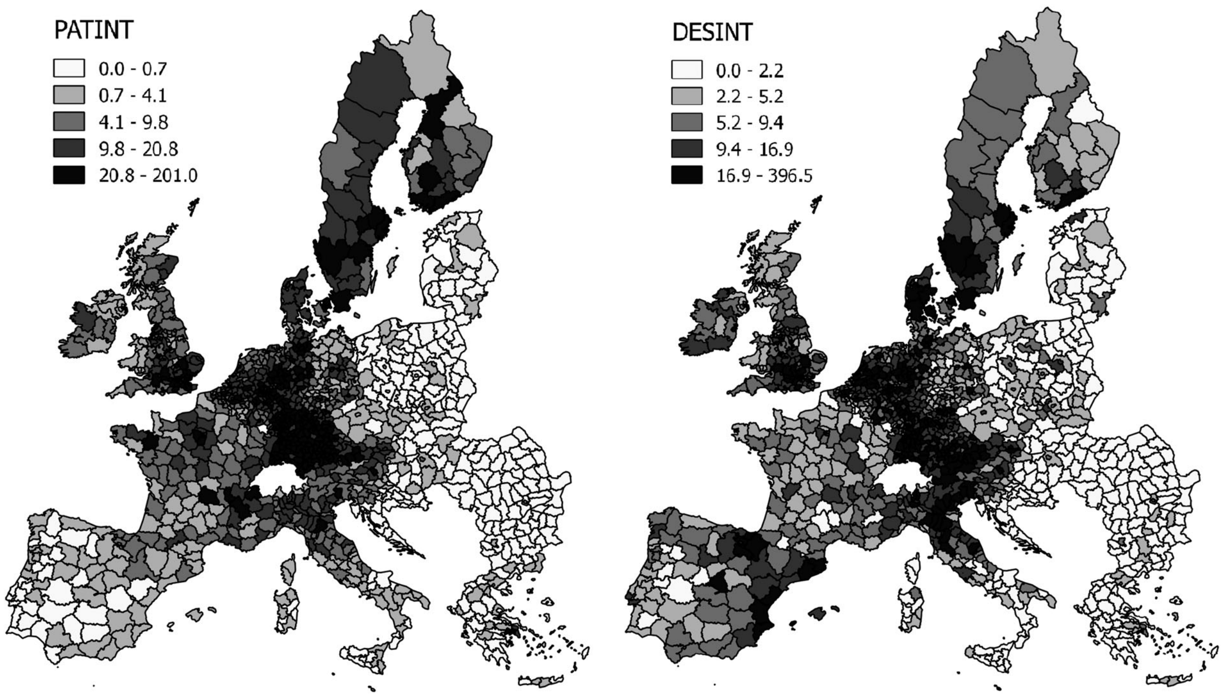

Figure 1. *PATINT* and *DESINT* across five quintiles: averages, 2000–12.

control for individual fixed effects induce bias in the typical ordinary least squares (OLS) estimation procedure because of the presence of lags of the dependent variables as regressors, which means that the fixed effects are inevitably correlated with the regressors (Nickell, 1981). To address this, we adopt the solution of Abrigo and Love (2015), applying the Helmert transformation (i.e., removing the mean of all future observations available for each pair of i and t) and then estimating the parameters simultaneously with the general method of moments (GMM). The Helmert transformation preserves the orthogonality between the variables and their lags allowing to use lags as instruments in a system-GMM estimation (Arelano & Bover, 1995).[4] The number of lags was selected considering various moment and model selection criteria (Andrews & Lu, 2001) satisfying Hansen's (1982) J-statistic of over-identifying restrictions and eigenvalue stability condition. These are reported in Table A1 in Appendix A in the supplemental data online. We also time-demean all series to control for time effects. Finally, we apply the Cholesky decomposition method to obtain contemporaneously uncorrelated errors across the variables. In this way we ensure that our inference will not be based upon composites of the two variable innovation terms. Instead, the shock of each endogenous variable is explicitly identified. This is a crucial step to interpret separately the effect of time dependence as endogenous growth and the effect of cross-dependence as co-evolutionary complementarities. With respect to the latter, it is worth noting that the PVAR model captures the positive (or negative) externalities, that is, the effect of complementarities; however, it remains agnostic as to whether such effects are through a direct combination of one type of knowledge with the other or result from spatial spillovers and learning effects across heterogeneous knowledge resources.

Inference in the PVAR framework is primarily drawn upon the so-called impulse-response functions (IRFs). It is a method adopted from signal processing to capture the response over time of each of the endogenous variables to a one period exogenous impulse (shock). In other words, the IRFs capture the evolution in the whole system of a one-period change of the innovation term or shock of each endogenous variable. This allows to visually depict in a unified way both the possible time dependence (i.e., regional path dependency) that technological change and design innovations may exhibit and their possible interdependence.

Overall, and in anticipation of the empirical results that follow, the best-fit model for the region i at time period t proved to be given by:

$$\begin{pmatrix} PATINT_{it} \\ DESINT_{it} \end{pmatrix} = \begin{pmatrix} PATINT_{it-1} \\ DESINT_{it-1} \end{pmatrix} A_1 + \begin{pmatrix} EDUC_{it} \\ DENS_{it} \\ TDIV_{it} \\ GDPg_{it} \end{pmatrix} B + u_i + e_{it} \quad (2)$$

where the vector of the dependent variables includes the standardized values of *PATINT* and *DESINT*, with the former referring to the number of patent applications to the EPO by total population for each NUTS-3 region, while *RCDINT* and *TDMINT* being, respectively, the total number of RCD and trademark applications to the EUIPO, also normalized by total regional population.[5]

Finally, despite the fact that the modelled dynamics of the endogenous variables and the included region-specific fixed effects should suffice to control for unobserved heterogeneity, we also include the vector of control variables B_{it} to provide further robustness. Here, we have the variable *EDUC*,[6] defined as the percentage of people with a tertiary degree to control for human capital, population density expressed as population per km^2, labelled *DENS*, and a proxy of diversification in the regional structure, labelled *TDIV*,[7] measured using an entropy index at the Standard Industrial Classification (SIC) three-digit level. Finally, we add ΔGDP, representing the change of regional gross domestic product adjusted to purchasing power parity (PPP), to control for demand dynamics in the regional economy.

A statistical overview of the properties of all variables is presented in Table 1, reporting the main descriptive statistics, and Table 2, reporting the correlation matrix.

5. RESULTS AND DISCUSSION

To explore the presence of persistent innovation effects and potential synergies between design innovation and technological change, we start exploring the bivariate PVAR model where we consider two shocks coming separately from the innovation term of *PATINT* and *DESINT* equations. The orthogonalized IRFs for the bivariate PVAR model are reported in Figure 2.[8] To facilitate comparison, we have standardized values so that IRFs show how each of the dependent variables reacts over time to an instantaneous change by 1 SD (standard deviation) of one of the innovation terms at some zero/initial point in time.

Table 1. Descriptive statistics.

	PATINT	*RCDINT*	*TDMINT*	*EDUC*	*DENS*	*TDIV*	*ΔGDP*
Mean	1.35	0.31	1.04	22.82	584.53	0.81	236.1
SD	1.85	0.37	1.67	7.93	1400.2	0.21	941.3
Skewness	3.1	4.2	11.8	0.3	6.2	−2.6	3.3
Kurtosis	20.0	35.0	229.3	3.4	59.4	9.9	65.4

Table 2. Correlation matrix.

	PATINT	*RCDINT*	*TDMINT*	*EDUC*	*DENS*	*TDIV*
RCDINT	38%					
TDMINT	45%	47%				
EDUC	15%	5%	19%			
DENS	6%	8%	25%	19%		
TDIV	28%	19%	24%	12%	7%	
ΔGDP	4%	6%	15%	9%	22%	6%

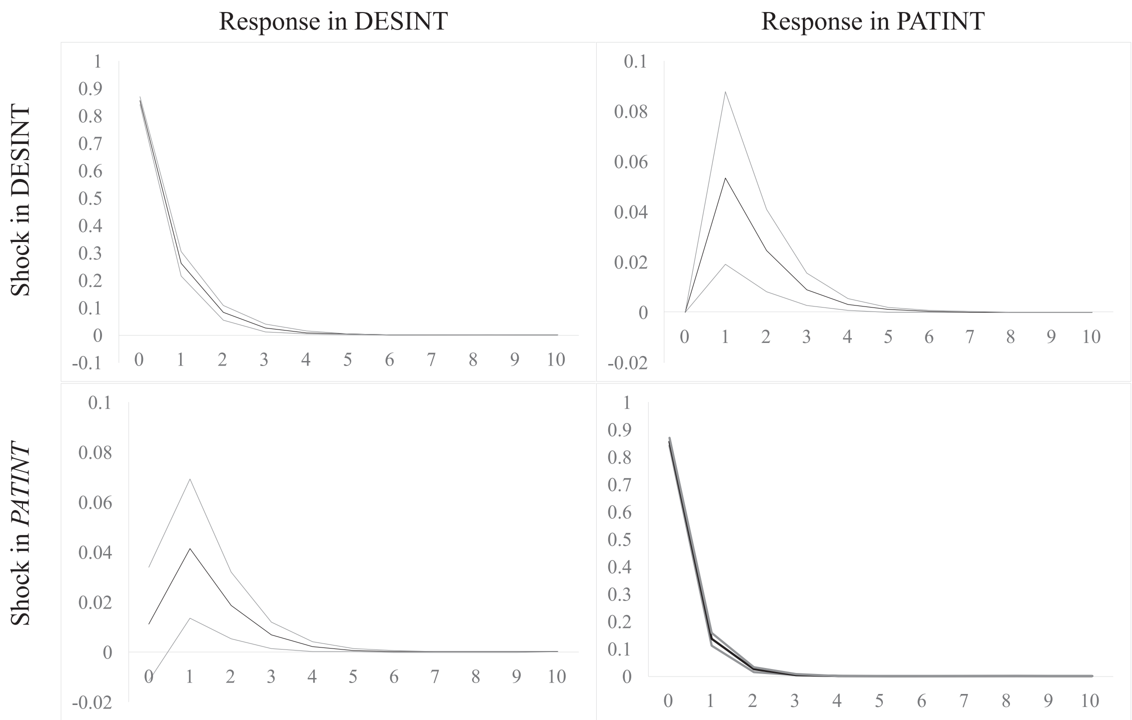

Figure 2. Orthogonalized impulse response functions (IRFs): bivariate panel vector autoregression (PVAR).
Note: Graphs are based on the best-fit model selected by the *J*-test and the model information criteria.

With regards to the presence of time persistence in the *PATINT* variable (Hypothesis 1a), depicted in the bottom-right corner IRF graph, we observe a marked effect which is positive and statistically significant. The time persistence of *DESINT*, depicted in the top-left IRF graph in Figure 2, is also positive and statistically significant, in line with Hypothesis 1b. In both cases, the effects seem to last around two to three years independently of the lag structure. While the PVAR model is not designed to offer insights on long-run trajectories of innovation, the results underline the presence of endogenous dynamics so that regional innovation output is more than just the sum of innovation in any particular year, due to positive learning effects when output increases. This creates important incentives and positive returns for regions catching up. However, as indicated by previous literature (Fagerberg & Godinho, 2005; Lee, 2019), only a constant effort at sustaining innovation capabilities will define long term trajectories. In the setting of our model, this would correspond to a sequence of positive shocks – instead of the single one depicted in each case. These results confirm previous descriptive evidence of persistence in patenting rates across regions (Breschi, 2000; Soo, 2018); also, they extend the discussion of localized cumulative dynamics (Martin & Sunley, 2006) to other types of knowledge bases beyond technological change, such as design. These findings underline the link between the literature on differentiated knowledge bases and place-based perspectives for regional innovation (Asheim, 2007; Capello, 2017), suggesting regions may build dynamic returns and competitive advantages on different forms of innovation capabilities. This may be particularly important for regions with limited resources in technology-intensive R&D activities (Lee, 2019).

Figure 2 also shows complementarity effects between *PATINT* and *DESINT*. In line with Hypothesis 2, these are found to be mutually positive and statistically significant for both endogenous variables in the system. However, the impact of time dependence in terms of determining both *PATINT* and *DESINT* variables is distinctly more pronounced than the impact of their interdependence. This bidirectional nature of the causality between technological change and design innovation can also be observed when testing for the direction of the (predictive) causality with PVAR Granger-causality Wald tests (reported in Table A2 in Appendix A in the supplemental data online).[9] Indeed, the tests confirm the simultaneous and complementary effects that each type of innovation activity exerts on the other. Therefore, these findings overall extend previous insights on innovation as a process of recombination within the regional technological space (Boschma & Martin, 2010; Kogler et al., 2017). While our results do not necessarily imply a direct combination of design within technological invention, they point to significant spillovers and systemic learning effects, highlighting synergies across different dimensions of innovation activities and knowledge competencies as reflected by the duality of technological and design activities (Asheim et al., 2007; Camagni & Capello, 2013; Grillitsch et al., 2017). Recent research has underlined how different types of intellectual property (IP) protection can be used to capture different forms of innovation, with design and trademarks in particular working as proxies for innovation in services, low-tech manufacturing and creative industries (Block et al., 2021; Castaldi, 2020; Filitz et al., 2015). Our results add to these insights, pointing to important interdependencies and co-evolutionary complementarities (Fritsch et al., 2019) occurring across these different forms of knowledge creation within regional innovation systems.

Underlying the analysis of IRF graphs, the coefficient estimates of all models – reported in Table 3 – confirm the presence of persistence effects and the mutually dependent relationship between technological change and design activities. In particular, the coefficient estimates of the lags of the dependent variables show a substantial degree of statistically significant time dependence both for *PATINT* and for *RCDINT* in the bivariate models. Likewise, based on estimates of the cross-equation lags we also observe significant interdependence. Table 3 also shows coefficients for models with lags of order two and three, which yield consistent results with the IRFs presented above.

With regards to the control variables, we observe *EDUC* is statistically significant in all equations. However, its effect on *PATINT* is negative. In line with recent studies (Apa et al., 2018), this may reflect different effects of tertiary education subjects. Hence, it is possible the lag structure of *PATINT* may be effectively capturing within-variation of technology-related human capital effects. Accordingly, the relationship in the correlation matrix (Table 2) shows consistently a strong and positive connection between these metrics. In the same spirit, we observe *DENS* is statistically significant but negative for *PATINT*. While urbanization economies are linked to higher density, suggesting stronger interaction effects, recent papers have indicated this may not be necessarily the case for technological development, which is less reliant on urban creativity and may actually suffer due to congestion and higher costs for manufacturing activity (Apa et al., 2018; Dijkstra et al., 2013). Finally, technological diversification (*TDIV*) is found to have a substantial and statistically significant positive effect on *PATINT*, in line with previous literature (Castaldi et al., 2015; Corradini & De Propris, 2015). In contrast, ΔGDP seem to have a small and positive impact, but this is statistically insignificant in models with lags of order 1. This changes when including further lags, which may reflect its more complex, long-term effect on innovation.

In Figure 3 we further disentangle the specific aspects of design innovation. Whilst patents strongly relate to analytical knowledge bases and RCDs are inherently rooted in symbolic knowledge, the role of trademarks may be more ambiguous. On one side, trademarks have a strong symbolic function and may capture reputational assets, branding as well as creative activities (Castaldi, 2020). On the other side, they have also been associated

Table 3. Panel vector autoregression (PVAR) bivariate results.

Variable	PVAR(1)		PVAR(2)		PVAR(3)	
	Eq. PATINT	*Eq. DESINT*	*Eq. PATINT*	*Eq. DESINT*	*Eq. PATINT*	*Eq. DESINT*
$PATINT_{t-1}$	0.29*** (0.03)	0.06*** (0.01)	0.24*** (0.02)	0.04** (0.02)	0.23*** (0.03)	0.02 (0.02)
$PATINT_{t-2}$	–	–	0.13*** (0.02)	0.02 (0.02)	0.11*** (0.02)	−0.01 (0.02)
$PATINT_{t-3}$	–	–	–	–	0.13*** (0.02)	0.01 (0.02)
$DESINT_{t-1}$	0.13*** (0.03)	0.23*** (0.02)	0.14*** (0.02)	0.21*** (0.02)	0.18*** (0.03)	0.17*** (0.02)
$DESINT_{t-2}$	–	–	0.12*** (0.02)	0.08*** (0.02)	0.12*** (0.03)	0.05*** (0.02)
$DESINT_{t-3}$	–	–	–	–	0.1*** (0.02)	0.03* (0.02)
EDUC	−0.17*** (0.01)	0.15*** (0.01)	−0.24*** (0.01)	0.11*** (0.01)	−0.3*** (0.02)	0.1*** (0.02)
DENS(+)	−0.25** (0.12)	0.05 (0.06)	−0.21* (0.12)	0.07 (0.08)	−0.24 (0.18)	0.05 (0.09)
TDIV	6.69*** (1.76)	−1.45* (0.74)	4.66*** (1.14)	−1.41 (0.87)	4.64*** (1.71)	−1.46 (1.19)
$\Delta GDP(++)$	0.25 (0.17)	0.04 (0.10)	0.44*** (0.15)	0.2** (0.09)	0.67*** (0.17)	0.26*** (0.10)
Regions	938	938	861	861	801	801
Observations	5829	5829	4818	4818	3934	3934

Note: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$; *t*-statistics, in parentheses, are based on robust standard errors. All models include time and regional fixed effects. Shaded areas indicate the results based on the best-fit models selected by the *J*-test and the model information criteria.

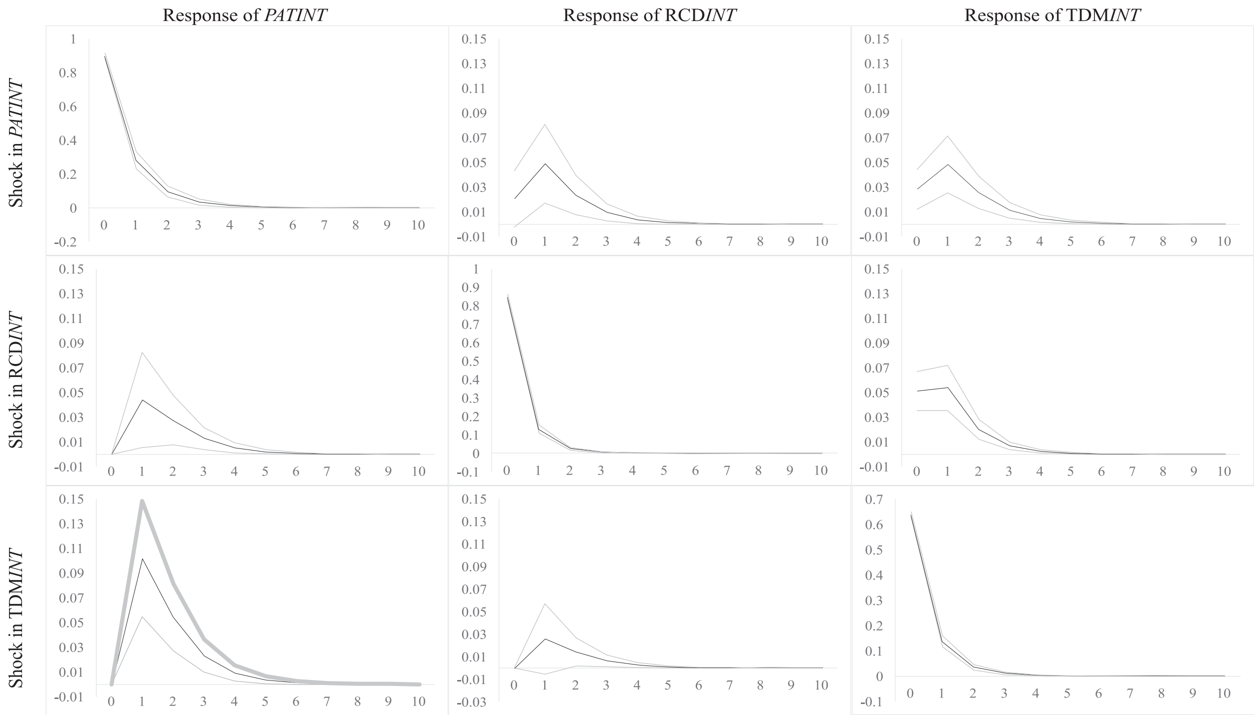

Figure 3. Orthogonalized impulse response functions (IRFs): trivariate panel vector autoregression (PVAR).

with synthetic knowledge bases due to their connections to downstream capabilities (Asheim et al., 2011; Castaldi, 2020) and knowledge-intensive business services (KIBS) activities (Block et al., 2021). To this end, we explore a trivariate PVAR model[10] where we consider three shocks coming separately from the innovation term of *PATINT*, *RCDINT* and *TDMINT* equations. In line with the results from the bivariate model, the IRFs for each shock and endogenous variable show the presence of strong path dependence across all three dependent variables indicating the presence of dynamic increasing returns for the three measures of innovation intensity.[11]

With respect to complementarity effects, we confirm significant effects across all three variables with the exception, albeit marginally, of *TDMINT* on *RCDINT*. Complementing recent evidence on trademarks (Drivas, 2020) and their potential role of as proxy for innovation in KIBS, whose activities are directed at stimulating knowledge transfer and innovation at clients (Block et al., 2021), we also note the effect of *TDMINT* is particularly marked on *PATINT*. We also observe the reverse effect, though this is less prominent. Overall, the magnitude of the interdependence is again smaller than that of the time dependence; nevertheless, it is still substantial and statistically significant.

As noted when discussing the bivariate PVAR, these results underline potential learning effects from creative activities towards other forms of innovation (Lee & Drever, 2013; Lee & Rodríguez-Pose, 2014). More broadly, these findings emphasize how different forms of innovation reflecting technological invention, soft innovation as well as innovation in services and small and young firms (Block et al., 2021; Castaldi, 2020), may all spur significant synergies leading to increasing returns for regional innovation. This reinforces previous insights on the multidimensional nature of innovation in regions, and the co-evolutionary complementarities that arise where differentiated knowledge bases are connected in the locality (Asheim et al., 2011; Asheim et al., 2017; Fritsch et al., 2019). These results are also confirmed in the respective Granger causality tests, reported in Table A2 in Appendix A in the supplemental data online.

5.1. Robustness analysis

In this section we explore whether inherent differences in regional innovation systems affect our results, in terms of heterogeneity of findings across (groups of) regions. To this end, we run the bivariate PVAR model across a split sample to examine potential differences: (1) in the quality of institutions which we measure using the European quality of government index (EQI), based on the QoG EU Regional dataset adopted in previous studies on the role of institutional quality for regional innovation (Charron et al., 2014; Rodríguez-Pose & Di Cataldo, 2015); and (2) in the strength of entrepreneurial ecosystems proxied using the regional entrepreneurship and development index (REDI) developed by Szerb et al. (2013) as a composite measure based on 40 indicators reflecting entrepreneurial attitudes, abilities and aspirations of different dimensions at the regional level.

Figure 4 depicts the respective IRFs,[12] each drawn from the best-fit bivariate PVAR. Overall, the effects identified are aligned with our main results. We find again for both groups of regions evidence of strong persistence for *PATINT* and *DESINT*. The similarity in the impulse-response graphs between stronger and weaker

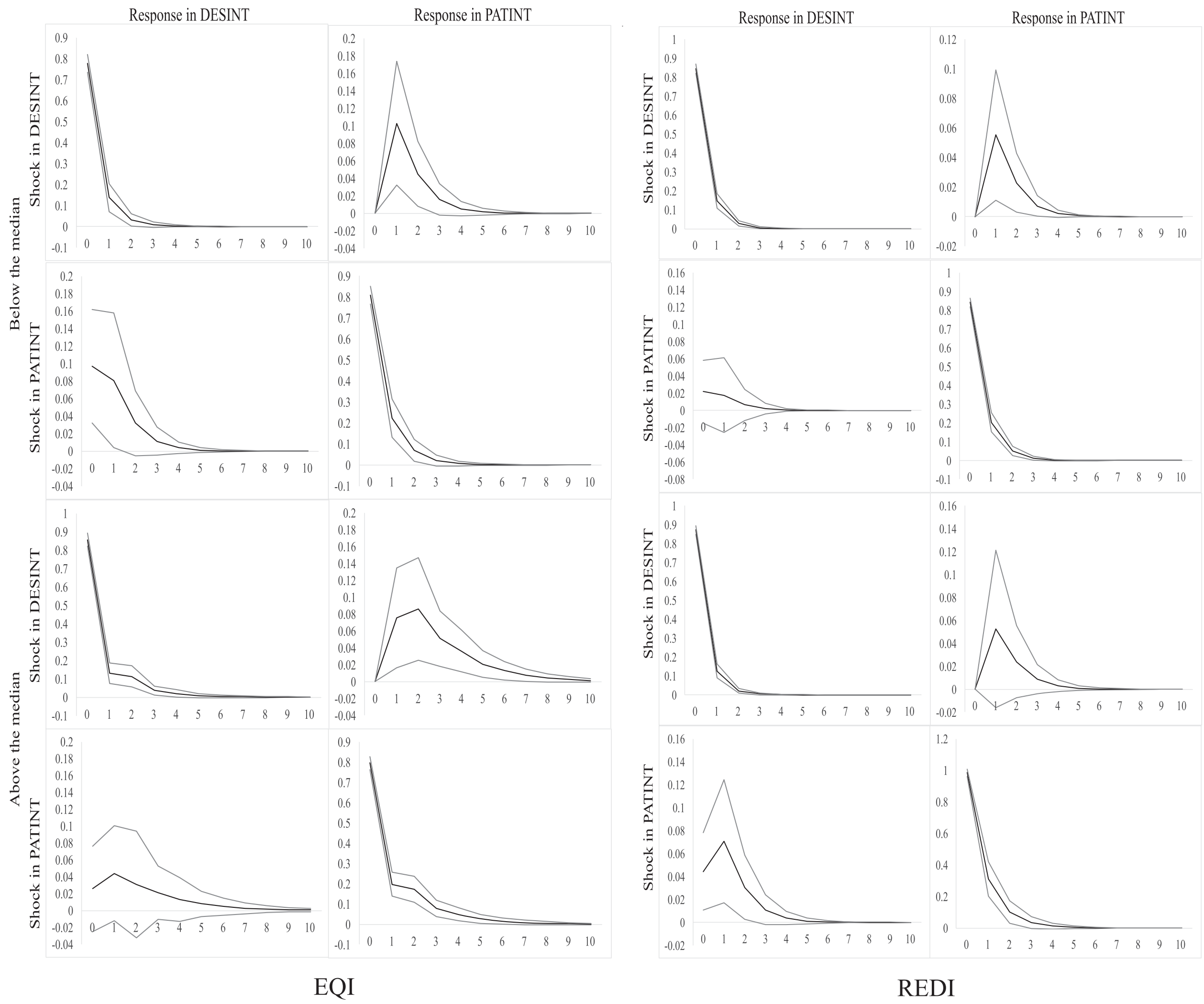

Figure 4. Panel vector autoregression (PVAR) for above and below median quality of government index (EQI) and regional entrepreneurship and development index (REDI) regions.

regions in both quality of institutions and entrepreneurial ecosystems suggests stronger regions will continue reaping similar benefits from a shock in patents and/or designs as the weaker ones. Stronger institutions and networks may counterbalance diminishing returns in learning effects for patents or design innovation; at the same time, these findings imply a positive shock in innovation may yield proportional returns in less developed regions. This provides important incentives to engage in both forms of innovation for these regions, reiterating the importance of investing in structural capabilities for sustaining long-run innovation trajectories (Fagerberg & Godinho, 2005; Lee, 2019). Indeed, it is on this aspect that stronger institutions may play a critical role.

We observe more differences in the complementarity effects. In regions with below-median quality of institutions, patenting activities are substantially affected by the regions' design intensity while the variability of former brings a less marked effect at the boundaries of statistical significance. These effects are similar in regions that exhibit above-median quality of institutions, though the effect of *PATINT* on *DESINT* is clearly not statistically significant. While it is important to consider the reduction in observations for this analysis, these findings suggest that while quality of regional government may be an important element for innovation (Rodríguez-Pose & Di Cataldo, 2015), its role on learning effects between technological change and design innovation are less defined.

Finally, Figure 4 shows that in regions with values below-median of the REDI index of entrepreneurial ecosystems *DESINT* has a statistically significant impact on *PATINT* while the reverse has not. In contrast, in regions that exhibit above-median values of the REDI index the effect of *DESINT* on *PATINT* is no longer significant, while we observe a positive and significant effect of patenting on design intensity. This suggests that strong entrepreneurial ecosystems play an important role in translating technological invention into other forms of innovation. At the same time, they may partially substitute for the positive effect of a shock of *DESINT* on *PATINT*. In less developed entrepreneurial ecosystems, the opposite may hold: these regions may struggle to absorb learning opportunities from patents; yet, an increase in soft innovation also associated with younger firms and KIBS

(Block et al., 2021; Castaldi, 2020) may spur capabilities to enhance technological change.

6. CONCLUSIONS

This paper has explored the evolutionary dynamics of technological change and design activities across EU regions, extending the hypothesis of spatial path dependence and localized cumulative effects for both layers. Furthermore, our analysis offers novel evidence of a synergic relationship connecting dynamic increasing returns from design and technological change, pointing to important complementarities across their different knowledge bases within regional systems of innovation. These insights are tested employing a panel vector autoregressive framework, where design and technological change are defined as endogenous within the system, on a dataset of over 900 NUTS-3 regions in Europe for the period 2000–12.

Several theoretical and policy implications emerge from these findings. The presence of spatial persistence in design innovation confirm cumulative dynamics are not confined within firms but they may also characterize the relational structure of regional innovation systems. Similarly to technological change, the presence of localized cumulative patterns in knowledge creation for design innovation also points to evolutionary dynamics that may lead to self-reinforcing effects for places that have been able to expand their design activities. This may support different trajectories of specialization across European regions, consistent with their diverse knowledge bases and territorial patterns of innovation (Asheim et al., 2007; 2011; Camagni & Capello, 2013). This also underlines regions do not need to have marked technological capabilities to engage in innovation, emphasizing different potential pathways for endogenous growth in regional development.

At the same time, our results indicate the presence of significant advantages for places that are active on both dimensions of innovation. This underlines the synergies and complementarities that may occur across the whole regional innovation system, transcending various knowledge bases spanning from scientific and technical to symbolic functions (Asheim et al., 2011). This provide evidence in support of previous calls for a more heterogeneous analysis of regional innovation patterns, beyond perspectives equating knowledge creation to scientific research (Camagni & Capello, 2013; Capello, 2017). Similarly, we join recent research stressing the need to explore different forms of IP rights, including design and trademarks, to capture a more comprehensive picture of regional innovation activities and better understand the important complementarities these may define within regional knowledge networks (Block et al., 2021; Castaldi, 2020; Drivas, 2020; Filitz et al., 2015). These findings support and reinforce perspectives of innovation as combinatorial activity (Boschma & Martin, 2010), extending previous insights looking at processes of recombinant knowledge across related technological activities to the broader set of interactions and connections across differentiated knowledge bases (Asheim et al., 2011; Grillitsch et al., 2017).

From a policy perspective, the results presented stress once again the need to explore different metrics when evaluating innovative capabilities of regions, explicitly recognizing technological change as one of many layers of regional innovation. In line with recent critique of Smart Specialisation policies as being too reliant on science and technology models of innovation (Hassink & Gong, 2019), increasing attention towards other forms of innovation, as design or trademarks, may be an effective policy objective in its own right, especially for regions that present related capabilities and may build on previous accumulated knowledge in this area. More importantly, our findings underline policies for technology and design innovation should not be defined in isolation, but through a multilayered perspective where cross linkages and synergies are emphasized and encouraged across the whole system of innovation.

The findings presented should be interpreted considering the usual caveats in the analysis of patent data, which should be extended to the use of RCDs and trademarks in this study. In particular, the insights offered in the paper may not necessarily apply to new technologies or designs that are not covered by formal methods of intellectual property protection. We also point out the need for further evidence on spatial determinants and dynamics in design activities beyond the cumulative effects explored in our model. At the same time, more research is required to disentangle the scale of complementarity and combinative dynamics. Our analysis builds on the assumption of co-location for learning effects and knowledge recombination through regional innovation systems. More research is needed to explore whether one type of knowledge is combined directly with another as recently shown at firm level (Corradini & D'Ippolito, 2022), or whether spillovers across different knowledge bases knowledge occur through external collaborations and distributed knowledge networks. Furthermore, while we consider different layers of regional knowledge creation, linkages to broader innovation activities require further analysis to provide a more comprehensive picture on territorial patterns of innovation (Capello & Lenzi, 2014). Similarly, insights on the relationship between different knowledge bases and regional growth remain scant (Grillitsch et al., 2017). The same applies to the importance of integrating symbolic knowledge as a source of new path development (Asheim et al., 2017). We underline these are important avenues for future research.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors .

NOTES

1. Results are robust when defining regions at the NUTS-2 level.
2. Differently from patents, RCDs are valid for five years, but they can be renewed for a maximum of 25 years.

3. While the inclusion of fixed effects is necessary for the correct estimation of the PVAR model, potential issues that may arise when within-variation is low with respect to between-variation are not a significant concern here. Indeed, in our data, the former is on average about 35% higher than the latter when measured as the average sample variances.
4. Innovation persistence is captured directly through the combination of fixed effects and the so-called memory of the stochastic process (the lag structure of Y_{it}). This is why, for example, incorporating Y_{i0} as the regressor, a common practice in other settings to capture path dependence as regional-specific deviations from the initial levels, yields identical results in a PVAR – in essence, it only decomposes the u_i term.
5. As a robustness check, we also perform the analysis further normalizing the endogenous variables by the level of GDP (PPP). The results are fully robust to this specification, and available upon request.
6. Using an alternative proxy based on the percentage of employees employed in science and technology sectors yields consistent results.
7. An alternative specification with measures of related and unrelated variety, defined at one- and three-digit International Patent Classification (IPC) class, was also explored. The results are robust to this approach.
8. The confidence bands of the IRFs, which are generated by Monte Carlo simulations following Love and Zicchino (2006), can be conveniently thought of as acting as the counterpart to statistical significance of coefficient estimates in a standard regression analysis.
9. Consistent results are obtained by using the Cholesky forecast-error variance decomposition.
10. This model is formally defined as:

$$\begin{pmatrix} PATINT_{it} \\ RCDINT_{it} \\ TMDINT_{it} \end{pmatrix} = \begin{pmatrix} PATINT_{it-1} \\ RCDINT_{it-1} \\ TMDINT_{it-1} \end{pmatrix} A_1 + \begin{pmatrix} EDUC_{it} \\ DENS_{it} \\ TDIV_{it} \\ \Delta GDP_{it} \end{pmatrix} B + u_i + e_{it}.$$

11. Coefficient estimates are reported in Table A3 in Appendix A in the supplemental data online.
12. Coefficients and Granger causality tests are available from the authors upon request.

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