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FULL ARTICLE

The effect of cultural and creative production on human capital: Evidence from European regions

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Abstract

Cultural and creative production (CCP) can create, renovate, and shape places' socio-economic environments. Recent contributions suggest that culture can activate a set of cognitive and productive mechanisms that form the basis of human capital (HC) dynamics. Bridging these two streams of research, the present paper investigates possible causal relationships between CCP and HC at the regional level. Empirically, we used measures of employment in the cultural and creative sectors as proxies for CCP and applied generalized method of moments (GMM) panel estimations to yearly data from 283 European NUTS 2 regions from 2014 to 2020. The findings suggest that CCP positively affects regions' average levels of HC even controlling for several economic and demographic factors.

KEYWORDS

Cultural and creative industries, cultural and creative production, employment, European NUTS 2 regions, human capital, regional economic development

JEL CLASSIFICATION

E24, R10, Z10

1 | INTRODUCTION

It is well known that intangible factors, such as endowments of human capital (HC) or outputs of cultural and creative activities, influence places and regions differently. First, HC has been considered a factor in location decisions (Storper & Scott, 2009), regional innovation (Felsenstein, 2011; Lee et al., 2010), regional differences in development

(Gennaioli et al., 2013; Marrocu & Paci, 2013), interregional migration flows (Faggian et al., 2019), and long-term policies for regional economic development (Mathur, 1999). However, learning processes, education, and training (and thus HC) levels may be influenced by place specificities and be critically related to regional socioeconomic dimensions (Bode & Perez Villar, 2017; Gennaioli et al., 2013).

Second, cultural and creative activities can influence local and regional employment (Boschma & Fritsch, 2009; Marlet & Van Woerkens, 2007), regional wages (Florida et al., 2008), interregional migration flows (Rodríguez-Pose & Ketterer, 2012), regional attitudes to job search (Eugster et al., 2017), local and regional entrepreneurship (Huggins & Thompson, 2016), regional tourist flows (Panzera et al., 2021), regional creation of new sector specializations (Cicerone et al., 2021), and general local and regional development (Bellandi et al., 2020; Cooke & Lazzeretti, 2008; Mommaas, 2004). Indeed, creative and cultural industries are often locally clustered, and they are heterogeneous across cities and regions (Garcia et al., 2018; Lazzeretti et al., 2012). Their heterogeneity in terms of industrial composition and market orientation (Tomczak & Stachowiak, 2015) tends to reproduce different sociocultural-driven environments that are identifiable at the regional level (Backman & Nilsson, 2018; Crociata et al., 2020).

Recent economic literature (Crociata et al., 2020; Tubadji et al., 2022), influenced by cognitive psychologists and neuroscientists (Pinker, 1997), has considered the positive relationships between culture and individuals' cognitive functions and analysed the role that culture plays in determining individuals' skills and capabilities. Extending the concept of cultural capital has led to an examination of the impact of culture or cultural participation (i.e., the impact of cultural demand possibly interlacing with proactivity; Crociata et al., 2020) on the endowment of places' HC. The study of this impact, complemented by assessments of feedback, is clearly important and forms a bridge between the two streams of regional research mentioned previously.

Herein, we aim to strengthen this bridge, focusing on the place-based supply side of cultural and creative activities (not only those at the cultural core), goods, and services, and its role to help produce or reproduce rich cultural and creative environments in which cultural participation and other related channels favour the growth of HC. More precisely, we refer to the activities, products, services, and content provided by agents and firms that are active within the cultural and creative production (CCP) sectors. Nowadays, such sectors have direct economic impacts by, for example, employing roughly 7.2 million people in Europe (3.6% of the total workforce) in 2020, according to Eurostat[1] definitions and estimates. To our knowledge, what is lacking at present is an assessment of the impacts of CCP on HC dynamics, specifically those that develop at the local and regional levels. Therefore, our main research question (RQ) was formulated as follows: to what extent does CCP affect HC within and across regions? Related questions were as follows: what factors moderate this relationship, and is it meaningful to combine cultural and creative sectors in such assessments?

To unpack these issues, we first considered the conceptual premises that may justify the existence of place-based transmission channels from CCP to HC. Building on these premises, we conducted an empirical analysis based on a dataset of 283 European NUTS 2 regions over a period of 7 years between 2014 and 2020. We used employment data from the cultural and creative sectors as relevant proxies to measure CCP as the main independent variable, and data on the educational level and lifelong learning of people and workers as proxies for HC as the dependent variable. The data included a set of control and lagged variables suggested by the conceptual premises. We applied generalized method of moments (GMM) panel estimations to this data, which allowed us to account for endogeneity, autocorrelation, and fixed effects. Moreover, we pooled and analysed different subsamples according to the distribution of HC to highlight possible recurrences and differences within regions with high or low endowments of HC, following insights gained from the conceptual premises and the previous literature.

In this paper, Section 2 presents, together with a literature review, a conceptual framework for the relationship between CCP and HC at the regional level and proposes two related hypotheses. Section 3 describes the methodology, together with the variables' sources, construction, and descriptive statistics, and maps European

[1]https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Culture_statistics_-_cultural_employment

NUTS 2-level regions according to the main variables of interest. Section 4 presents and discusses the main findings of the empirical analysis. Finally, Section 5 provides the conclusion and suggests implications for policy and future research.

2 | LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 | HC and the economic development of places

HC has been at the core of economic debates for a long time. Even before Becker's *Human capital* (1964), economists were well aware of the importance of investing in individuals' or workers' education for economic development, that individuals' educational levels relate to their future earnings, and that education policy impacts economic growth and technological change (Bowman, 1996).

Certainly, HC is strongly affected by school and university education (Goldin, 2016), but it can also be developed at work through learning by doing and through job-specific training courses (Araújo & Pestana, 2017; Blundell et al., 1999). Related positive effects for work productivity, workers' earnings, and job assignments have been thoroughly investigated (Battu et al., 2003; Kwon, 2009), and, of course, research on the HC's general impacts on economic development and growth has been extensive, touching upon productivity, innovation, competitiveness, and other factors. (e.g., Barro, 2001; Becker, 1964, 1985; Becker et al., 1990; Hanushek & Woessmann, 2008; Marginson, 2019; Romer, 1990).

Regional science research efforts have focused on these topics (e.g., Faggian & McCann, 2009; Felsenstein, 2011; Lee et al., 2010; Mathur, 1999; Storper & Scott, 2009), building on longstanding reflections in the literature, such as those of Alfred Marshall on the industrial atmosphere in industrial districts. What interests us here is the formation and reproduction of pools of HC in places. In general, these depend on agglomerative factors from combined principles of learning by interacting in face-to-face contact, matching the demand and supply of skilled workers who have in aggregate limited long-range mobility, and the development of educational infrastructures and professional/vocational programmes oriented towards the needs of local industries (Duranton & Puga, 2004). These factors act at the level of cities, industrial districts, and other local productive systems (Bellandi et al., 2020). Larger regions (e.g., most NUTS 2 EU regions) may host different sets of local systems powered by agglomerative factors and possibly benefit from interactions between those local systems. Various features of local or regional contexts influence the strength of these factors and therefore the regional accumulation of HC. In what follows, we point out its relationship with cultural and creative features.

2.2 | Culture, creativity, and the economic development of places

Culture and creativity, and the relationship between them, are not exclusive to a single sector of activity (Cunningham, 2002; Lazzeretti & Capone, 2015). However, the main objective of some sectors rests entirely on care for, access to, and reappraisal of cultural heritage (the so-called cultural economy) or the creative use of cultural heritage to enhance the collective cultural and creative stock of places, including the enrichment or change of cultural heritage (the so-called creative industries; UNCTAD, 2010). This can also be extended to the presence of public and private structures that support the above-mentioned activities of cultural creativity, care, and participation (Bellandi et al., 2020; ISTAT, 2015).

It has been noted that, in principle, the cultural economy and creative industries follow different collective motivations, the first being more oriented to the public good or common side of culture, and the second to the extraction of private goods and returns from culture (Cooke & Lazzeretti, 2008). However, in contemporary societies and economies, increasingly driven by the production of analytical knowledge and the development of immaterial/digital goods and services, the borders between cultural and creative industries, and between them and other sectors, are becoming fuzzy (Lazzeretti, 2020; Sacco et al., 2018; Santagata, 2009).

We maintain that the growing intersections among cultural and creative industries allow us to adopt some common statistical definitions of their domains as the basis for empirical research. Nevertheless, interpretations of empirical results and the related policy implications should consider overlaps with broader domains and possible conflicts between public and private motivations within those domains. Tomczak and Stachowiak (2015) provided a detailed analysis of the heterogeneity of the cultural and creative sectors based on location patterns and market ranges. They found that the location patterns of cultural and creative industries differed. Industries that were part of the creative core, such as the videogame, film, and software industries, tended to be spatially clustered. Instead, cultural activities, such as the performing arts and architecture, tended to be more geographically dispersed (for the detailed topology, see Tomczak & Stachowiak, 2015). The former tended to have a global perspective, while the latter had a local perspective in terms of market access (museum vs. film/music streaming). Furthermore, Protogerou et al. (2017), analysing European firm-level data in creative industries, found that computer programming, consultancy, advertising, and publishing firms were likely to be concentrated spatially, but few of the industries specializing in architectural activities and technical design were concentrated. Mossig (2011), analysing employment changes in cultural and creative industries in Germany during 2003–2008, showed that the pace of change over time differed according to sector; for example, publishing firms observed reduced employment, whereas architecture, engineering, gaming, and software firms witnessed an increasing trend.

Finally, the boundaries of the cultural and creative industries and sectors are still a question under debate, often in relation to the specific perspectives adopted by researchers (Lazzeretti & Capone, 2015). The categorization of creative and cultural industries proposed by Eurostat's working group on culture statistics (Eurostat, 2019)[2] refers to CCP domains and proposes analyses at this aggregate level. It is the same level of data aggregation on which we based the empirical analysis described in the following sections. Less aggregated data do not currently seem to be available; hence, we assumed that this was a sensible basis for the analysis, although the results emerging from it need to be considered carefully.

As already explained in the introduction, contributions in regional science have argued about and investigated the presence of endowments of cultural heritage and related CCP as factors supporting the development of regions and places in association with various types of activation mechanisms (Cooke & Lazzeretti, 2008). CCP, with its place-based cultural heritage, can underpin paths of culture-driven growth, for example, in cities that depend on cultural tourism (Panzera et al., 2021). The endowment of cultural heritage can match, with the help of CCP, the demand for enhanced differentiation and authenticity based on local productive traditions (Bellandi et al., 2020). The combination of cultural heritage and CCP also favours a local but open-to-the-world creative atmosphere that fosters learning through the cross-fertilization of ideas between local and non-local nuclei of productive specialization, possibly leading to the emergence of new business ideas, entrepreneurial initiatives, and sectors (Bellandi & Santini, 2017; Boix Domenech & Soler-Marco, 2017; Cerisola, 2019; Cicerone et al., 2021; Crevoisier & Kebir, 2009).

Such activation mechanisms rely on human competencies and their adaptation; hence, we should consider the more direct impact of CCP on the factors that support the formation and evolution of HC in places.

2.3 | Hypotheses on the relationship between CCP and HC

Crociata et al. (2020) proposed an investigation of the "missing link" regarding cultural participation "as a source of human capital." As mentioned in the introduction, cultural participation concerns the demand for the products of

[2]These include the printing and reproduction of recorded media; printing and service activities related to printing; the manufacture of musical instruments; the publishing of books, periodicals and other publishing activities; motion picture, video, and television programme production; sound recording and music publishing activities; radio and television programming and broadcasting activities; specialized design activities; photographic activities; translation and interpretation activities; creative, arts, and entertainment activities; libraries, archives, and museums; and other cultural activities.

cultural and creative industries, although the authors argued that the growth and possibilities of active participation tend to combine supply and demand. They identified various transmission channels from cultural participation to HC, operating at either individual or collective levels, and the possibility of feedback and cumulative place-based effects.

At the individual/family level, there are two main transmission channels. On the one hand, cultural participation fosters the growth of mental plasticity, potential academic performance, and therefore incentives to invest in schooling. On the other hand, parents with high levels of cultural participation are likely to be included in segments of the population with higher levels of income/wealth, which tends to decrease the relative costs of schooling (see Bourdieu, 1986).

At the collective level, places with extensive opportunities for cultural and creative participation have two other related transmission channels. On the one hand, places featuring a vibrant cultural participation tend to attract talented and highly skilled people (see also Backman & Nilsson, 2018; Berry & Glaeser, 2005; Florida, 2005). On the other hand, participation in cultural events is a relational good built on the ability to share aesthetic appreciation and technical comments, and this capability expands levels of education, which can also be increased by lifelong learning.

Finally, Crociata et al. (2020) suggested that the actions of individual and collective transmission channels tend to accumulate differentially in places, given the situated nature of the processes involved, resting on the density of opportunities for contact. On this conceptual basis, they tested an econometric model using panel data for Italian NUTS 2 regions in 2004–2014, and found a positive relationship between HC, measured by the density of tertiary education and indices of lifelong learning, and cultural capital, measured by cultural participation indices.

The present paper aims to investigate more directly the supply side of cultural and creative content, based on CCP and its impact on HC, measured by levels of schooling and lifelong learning. Although there is no rigid distinction between supply and demand in culture and creativity, we focus on supply because it represents an organized productive process that aims to conceive, create, and deliver cultural items and incorporate them into goods and services with high cultural and creative content. In fact, as already mentioned, CCP refers to the production and reproduction of more permanent stocks of collective cultural and creative content (i.e., cultural heritage in its various expressions of territorial and social embeddedness; Drake, 2003; Becattini, 2015) and creative additions to such stocks (see footnote 2).

CCP can be measured in various ways, one of which is to consider cultural and creative entrepreneurship (i.e., the number of independent private and public organizations operating in related sectors; ISTAT, 2015). This is a good proxy for the internal variety of enabling innovative milieus and local cultural and creativity ecosystems. Another possibility is to consider the employment rate, which relates directly to the demand for HC. Indeed, it would be useful to use both types of measures. However, the large-scale empirical analysis that we undertook restricted us to employment data, given the lack of data on entrepreneurship at a sufficient level of sectoral detail.

There were two reasons for conducting an investigation that focuses on CCP's impact on HC as a useful complement to the work of Crociata et al. (2020). First, it allowed us to consider the impacts of some important transmission channels that measures of cultural participation could not adequately capture. We earlier addressed the possibility of path renewal and path diversification related to strong place-based CCP interacting with other local and non-local specializations (Cicerone et al., 2021). We have already inferred the necessity for adaptation in the pools of HC that such transformations demand. We add that culture-driven path transformation may demand not only an adaptation but also an aggregate upgrading of local HC pools. This could be satisfied by increasing the development of new skills, the capability to avoid local brain drain, and lifelong learning among local workers. Another transmission channel is represented by the composition of higher education necessary for CCP.[3] Higher education curricula in the

[3]Appendix Figure A3 shows the evolution of the rate of cultural and creative employment for people with an upper secondary education level, together with the yearly differences in educational attainment (as described in subsection 3.2) and cultural and creative employment compared with total employment for EU 27.

humanities and social sciences tend to be in greater demand in CCP than in many other economic sectors, apart from public administration. For example, 59% of the workforce employed in cultural and creative industries in EU 28 in 2018 had a tertiary education level that was higher than the average level across the entire economy (35%; Eurostat, 2019). All things being equal, this means more opportunity for local employment for people with higher education in non-STEM disciplines.

The second reason for directly considering CCP is that some of its activities can be devoted to non-local users/audiences. Although strong cultural participation (including that of cultural tourists) serves as a laboratory for CCP's competitive advantage in external markets, it is possible that parts of the HC produced by CCP in places will not relate directly or indirectly to local cultural events. Instead, there is the possibility that cultural events in places will be organized by external to the place CCP. The activation of HC by cultural participation in such events may still occur, but it seems more plausible that a concentration of cultural and creative opportunities, largely produced by local CCP agents, will directly promote the development of "a favorable social milieu (i.e., as a key enabling factor) for the formation of human capital" (Crociata et al., 2020, p. 87). Therefore, the first hypothesis (H1) that we developed concerned the following main relationship:

H1. Enhancing CCP generates an increase in HC at the regional level.

A related conceptual point concerns feedback, as suggested previously. CCP and HC are inherently interlinked. Regions hosting, on average, more educated people may host a larger number of cultural and creative activities because individuals who can process complex information, thanks to a previous accumulation of HC, are likely to benefit more from cultural and creative activities (Bourdieu, 1986; Throsby, 1999). Thus, CCP may have different effects on HC, depending on the previous accumulation of HC itself. In other words, higher endowments of HC may reinforce the influence of CCP on HC. In contrast, we may expect that CCP will have weaker effects on HC within regions with lower levels of existing HC. This has also been suggested and partly verified with respect to the relationship between cultural participation and HC in an Italian context (Crociata et al., 2020).

We formulated a second hypothesis (H2) about the impacts of such feedback as follows:

H2. Enhancing CCP generates a stronger increase in HC in regions with higher levels of existing HC, and vice versa.

The preceding discussion has suggested a set of other variables that can combine or interfere with CCP and HC. The first is, of course, cultural participation (Crociata et al., 2020), and the second concerns the presence of sectoral specializations that differ from CCP and measures of their evolution, relatedness, and complexity (Cicerone et al., 2021). However, given the extent of our empirical analysis, the first type of data was not readily available. The inclusion of the second type of variables was likely to increase endogeneity problems that were already affecting the main relationships, as it will be explained in the following sections. Both types of variables suggest routes for future research. In this paper, we just considered a set of control variables that were related, at least in aggregate terms, to the wealth and complexity of regional economies (e.g., GDP and *per capita* GDP) and their dynamics (rates of employment of people with higher education, and unemployment rates).

Finally, considering HC, it would have been useful to control for the local presence of educational structures and curricula, the various disciplines and fields of education, and the skill compositions of local productive specializations. We also had to defer the investigation of these aspects because of lack of data. Nevertheless, measures related to the age distribution of the population allowed us to control for the differential presence of people who had reached the end of their formal educational paths or who could benefit from higher returns on further investment in education.

3 | RESEARCH DESIGN

3.1 | Methodology and empirical context

We conducted multiple regressions by adopting GMM panel estimation[4] (Arellano & Bond, 1991). This method allowed us to both design a dynamic model to investigate the influence of CCP on HC at the regional level and to consider endogeneity issues (Roodman, 2009a).[5] GMM estimates have been used previously in regional studies (Arbia et al., 2008; Badinger et al., 2004; Crescenzi & Rodríguez-Pose, 2012; Gömleksiz & Özsahin, 2019), and specifically for investigating HC (Di Berardino et al., 2019). Since we elaborated on highly persistent dependent and independent variables at the regional level, we followed Arellano and Bover (1995) and Blundell and Bond (1998) by employing "system" GMM regression techniques.[6]

The dynamic model for estimation was as follows:

$$HC_{it} = \alpha_1 HC_{it-1} + \gamma CCP_{it-1} + \beta_1 X_{it} + \mu_t + \delta_i + u_{it},$$

where HC_{it} is the level of HC in region i at time t, CCP_{it-1} is a lagged (t – 1) variable as a proxy for the CCP of region i, X_{it} is the vector of control variables in region i at time t, μ_t and δ_i are the sets of time and regional fixed effects, and u_{it} is an error term, with $E(u_{it}) = 0$ for all regions i and times t. Time dummies made the assumption of no correlation across the groups (i.e., regions) regarding idiosyncratic errors more likely to hold (Roodman, 2009a).

The control variables dealt with the sociodemographic and economic features of places that might have an influence on the transmission channels between CCP and HC and support the endowment of HC, as mentioned at the end of subsection 2.3. They were the regional density of young people between 15 and 29 years old ($15\text{–}29_{it}$), the regional density of individuals between 30 and 40 years old ($30\text{–}40_{it}$), the regional median age (MA_{it}), the regional employment rate of people with secondary and tertiary education (EMP_{it}), the regional long-term unemployment rate (LTU_{it}), the regional gross domestic product at market prices ($GDPn_{it}$), and the regional gross domestic product at purchasing power standard per inhabitant ($GDPr_{it}$).

We included: (i) $15\text{–}29_{it}$ because it could intrinsically influence the level of education, mainly via schooling, and we expected it to have a positive effect on HC; (ii) $30\text{–}40_{it}$ as the portion of the population that was likely to be involved in training courses (e.g., in the workplace), and we expected a positive effect of this variable on HC; and (iii) MA_{it} because HC is inherently age dependent, and we expected that the older the region, the less HC would be endowed due to the increasing importance of education in the past half-century.

Concerning the transmission channels, we included: (i) EMP_{it} because regional economies with high employment rates of people with secondary and tertiary education favour the local accumulation of HC; (ii) LTU_{it} because it was likely to be positively associated with rates of participation in training for new job opportunities, but also negatively associated with HC due to the (possibly extensive) emigration flows typical of regions with high levels of

[4]The implementation of this regression technique exploits certain conditions: (i) "small T, large N" panels, meaning few time periods and many groups (i.e., regions); (ii) a linear functional relationship; (iii) a dynamic dependent variable; (iv) not strictly exogenous regressors; (v) individual fixed effects; and (vi) heteroscedasticity and autocorrelation within, but not across, groups (Roodman, 2009b). All these conditions were coherent in our study case.

[5]A few caveats are important here: (i) fixed effects are part of the error term of an untransformed level model; such a component may generate so-called dynamic panel bias due to correlations between fixed effects (in the error term) and the lagged dependent variable, but system GMM tackles this issue by transforming—differencing—the instruments, making them orthogonal to fixed effects (Roodman, 2009b); (ii) The Breusch–Pagan test (the version that drops the normality assumption) and the White test, following the linear regression, allowed us to control the existence of heteroskedasticity; moreover, we used a modified Wald statistic after the fixed-effects panel regression (Baum, 2001; Greene, 2000), which proved the presence of groupwise heteroscedasticity; and (iii) The Wooldridge test (Wooldridge, 2010) proved the existence of autocorrelation and implied the presence of inefficient and biased estimates under FE- and random-effects (RE) regressions. For these reasons, we preferred a GMM estimation model to deal with the features of the sample under investigation.

[6]A two-step procedure allowed us to improve the efficiency of the GMM estimator and the power of the associated tests. In fact, a two-step GMM estimator has smaller asymptotic variance than a one-step version (Hwang & Sun, 2018). Moreover, we adopted Windmeijer-corrected (2005) cluster-robust standard errors to obtain more accurate inferences.

unemployment; and (iii) *GDPn* and GDP per inhabitant ($GDPr_{it}$) as measures of the economic strength and productivity of a region, and, therefore of its wealth and complexity, suggesting a possible positive association with HC.

Finally, access to education might also be an important driver of HC at the regional level (Faggian et al., 2019). Although data on this issue were not available for all the observations included in our study, we partially captured this relationship by considering regional fixed effects as a set of regional characteristics that would be less prone to change during the period under investigation but heterogeneous across regions.

We investigated 283 NUTS 2 European regions over the period 2014–2020, for which we were able to obtain relevant and comparable data. This time span allowed us to capture the short-term activation mechanisms described in the theoretical framework. Even if long-term activation mechanisms operated plausibly over periods more extended than our time span, we would maintain the large cross-sectional dimension of the analysis and some inertia in the long-term trends of regional economic development, specifically in the accumulation of cultural and creative stocks, could allow us to make prudent references to long-term activation mechanisms in the interpretation of our results. We studied all the regions in Austria, Belgium, Bulgaria, Cyprus, Croatia, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Montenegro, the Netherlands, Norway, Poland, Romania, Serbia, Slovakia, Slovenia, Sweden, Switzerland, Turkey, and the UK. We identified some missing values; for example, data about UK regions were missing for 2020.

Finally, we added a specification to capture recurrences and differences across regions with different levels of HC according to its distribution (Tano, 2014). To do this, we built a dummy variable according to the following procedure: first, we computed the mean over time of the regional level of log HC in the period 2014–2020, and second, we coded regions with HC below the median level as 0, and 1 otherwise. Thus, we included an interaction between such a dummy variable, considering high and low levels of HC, and our core variables proxying for CCP.

3.2 | Construction of variables

Following Crociata et al. (2020), we computed HC as the product of the percentage of people who had achieved a specific education level and an index of lifelong learning. Specifically, we adopted two measures to distinguish levels of educational attainment: upper secondary (ISCED, 2011; ED3–8) and tertiary (ISCED, 2011; ED5–8).[7] Multiplying the percentage of people with either an upper secondary education (SE_{it}) or a tertiary education (TE_{it}) by the rate of participation in education and training (PR_{it}) allowed us to check for a causal mechanism based on the year-by-year rate of participation in training. It also allowed us to capture the complex dimension of (business- and school-driven) education using a full measure computed by multiplying the two variables to deal with the complementarities between them.

Formally, for the measure based on upper secondary education, $HC_{it} = SE_{it} * PR_{it}$. SE_{it} was the percentage of individuals who obtained at least an upper secondary education level in each region *i* at time *t*. PR_{it} was the rate of participation in education and training of individuals participating in the survey administered by Eurostat in the last four weeks from the time of the interviews in region *i* to time *t*. We included PR_{it} for all individuals in the population (not only upper-secondary educated people) because we were not interested in limiting the evidence to a "superclass" of well-educated individuals, CCP being a possible activator of learning mechanisms through training on the job irrespective of levels of education.

As suggested by Crociata et al. (2020), we also included a specification built on the percentage of individuals who achieved at least a tertiary education level ($HCter_{it}$). Formally,$HCter_{it} = TE_{it} * PR_{it}$. TE_{it} was the percentage of individuals who obtained at least a tertiary education in each region *i* at time *t*, and PR_{it} was the participation rate in training, as explained above.

[7]The International Standard Classification of Education (ISCED, 2011) categorizes educational levels from 0 (less than primary) to 8 (tertiary). ED3–8 included both upper secondary and tertiary education; ED5–8 referred only to tertiary education.

The hypothetical maximum level of HC_{it} was 10,000, meaning that the entire population had at least an upper secondary/tertiary education and had participated in education or training courses in the last four weeks. According to Gennaioli et al. (2013), this method of measuring HC refers to the quantity of HC in a specific region. To deal with relative changes in the variables, we applied a logarithmic transformation to both HC_{it} and $HCter_{it}$.

Finally, we also recognized the relevant role played by activation costs, which are inevitably higher for less educated people, and vice versa. For this reason, we divided the sample into two groups according to the mean level of HC, as previously introduced (i.e., one group included regions with a higher mean level of HC, and the other included regions with a lower mean level of HC).

We proxied CCP at the regional level of employment in the cultural and creative sectors (see footnote 2) by thousands of people. This econometric strategy also exploited the employment ratio in cultural and creative industries, based on the total number of employees in each region *i* at time *t*, as another relevant variable measuring the sectoral specialization (CCP_S) of regional economies.

The control variables were: $15–29_{it}$, $30–40_{it}$, MA_{it}, EMP_{it}, LTU_{it}, $GDPn_{it}$ *and* $GDPr_{it}$, as introduced in subsection 3.1. Data on all variables were collected from the regional statistics for NUTS 2 regions provided by Eurostat (2021).

3.3 | Descriptive statistics

Descriptive statistics of the variables included in the model are provided in Appendix Table A1. The within level represents intra-regional variability in the period under consideration, whereas the between level represents the interregional variability, encompassing the permanent and stable differences among observations. *N* represents the observation count, *n* is the number of considered regions, and *T-bar* is the mean number of available observations for each region. As the Table shows, the interregional variability was always higher than the intraregional variability, suggesting higher heterogeneity across regions for all our variables than heterogeneity over time. The correlation matrix for the variables is presented in Appendix Table A2. The highest values were between the proxies of HC and their lagged values, which was a sign of the high persistence of the data, as discussed previously.

Figure 1 shows a map of the regional logarithmic levels of CCP_i, $CCPs_i$ (on the right-hand side) and HC_i, and $HCter_i$ (on the left-hand side), computed as their mean values over time. Lower average levels of CCP_i and $CCPs_i$ are indicated in pale green, and higher average levels are indicated in blue. Lower average levels of HC_i and $HCter_i$ are shown in yellow, and higher average levels are shown in red. The lowest levels of CCP_i were in several peripheral Greek regions, whereas the highest levels were in Île de France, Istanbul, Lombardy, and Berlin. Thus, the role played by metropolitan cities might be relevant in increasing the extent of the labour force in cultural and creative industries. When dealing with the ratios of this measure, rural regions in Romania and Turkey had the lowest levels of specialized workers in the cultural and creative industries, whereas the highest levels were in Inner London, West Berlin, and Prague suggesting, again, the presence of a metropolitan city effect.

When considering HC, the results showed that levels of HC_i were sometimes similar within national boundaries. However, some particular occurrences must be reported. First, the lowest levels of HC_i were generally observed in Romania, followed by Bulgaria and Turkey. Second, in some countries, the regions presented diverging patterns; for instance, the southern regions of Italy had lower levels of HC than the northern and central Italian regions. Similarly, North Portugal had a lower level than other Portuguese regions, and the same was true for Champagne-Ardenne and Picardie compared with other French regions. Third, the highest levels were mainly in Switzerland and in several regions of Sweden, such as Stockholm and Östra Mellansverige, followed by other regions in Finland, Denmark, Sweden, the UK, and France. The map of $HCter_i$ revealed a similar picture but only for some concentrated pools of tertiary-educated people. In absolute terms, the highest levels were in the Nordic regions, the UK, Switzerland, the Netherlands, France, and Iceland. The lowest levels were in the Romanian, Bulgarian, Greek, and Turkish regions. As mentioned previously, there was also quite large within-country variability (e.g., in Italy, Portugal, Spain, and Turkey).

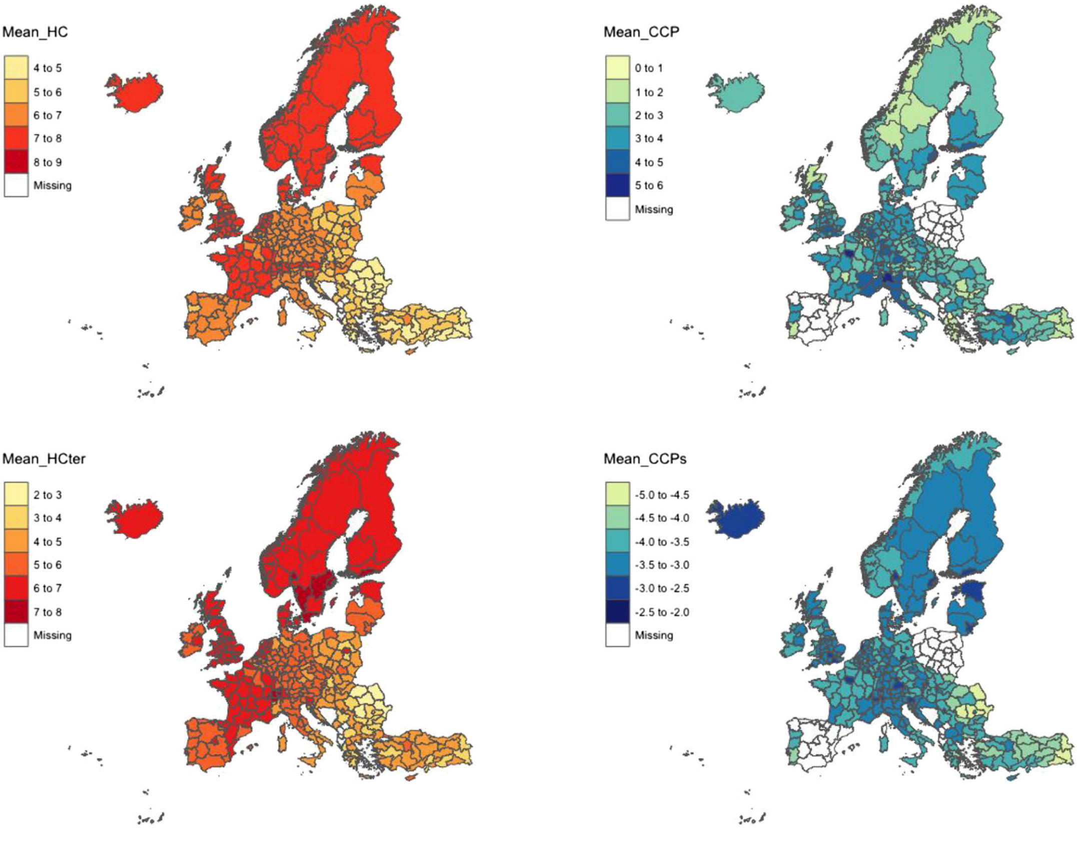

FIGURE 1 Mean of *HC* and *CCP* over time (2014–2020) across European regions. *Notes*: *Mean HC* and *Mean HCter* are the mean values over time of regional logarithmic levels of human capital based on upper secondary and tertiary education, respectively. *Mean CCP* and *Mean CCPs* are the mean values of the regional logarithmic levels of employment in the cultural and creative sectors and the employment ratio of cultural and creative industries to the total number of employees, respectively. Construction of variables is reported in subsection 3.2. *Source*: our elaboration on Eurostat (2021).

Maps of the regional logarithmic levels of CCP_{it}, $CCPs_{it}$, HC_{it}, and $HCter_{it}$ in 2014 and 2020 (i.e., the first and last years of our study period) are included in Appendix Figures A1 and A2. They provide a comparison in time of the phenomena under study.

Possibilities of causal interpretations of the phenomena under study are discussed in the next section.

4 | RESULTS AND DISCUSSION

The results of the empirical analysis, which followed an iterative process, are shown in Table 1. Column (1) presents estimates of pooled ordinary least squares (POLS) regressions, and column (2) presents those of fixed-effects (FE) regressions. Other columns specify different models based on a two-step system GMM technique, in which we considered all possible issues due to heteroscedasticity, fixed effects, disturbances'autocorrelations, and the persistence of the dependent variable. Specifically, column (3) shows estimates computed with CCP_{t-1} treated as endogenous; column (4) adds several control variables (including $EMP_{it,}$ $GDPn_{it}$ *and* $GDPr_{it}$, which were treated as endogenous); column (5) adds an interaction term between our core variable and regions with high endowments of

TABLE 1 GMM regression results on HC

	(1) Pooled OLS	(2) Fixed effects	(3) Sys-2 GMM	(4) Sys-2 GMM	(5) Sys-2 GMM	(6) Pooled OLS	(7) Fixed effects	(8) Sys-2 GMM	(9) Sys-2 GMM	(10) Sys-2 GMM
Dependent variable is Log (HC_t)										
Log (HC_{t-1})	0.971*** (0.0050)	0.344*** (0.0535)	0.665*** (0.1762)	0.814*** (0.2325)	0.730*** (0.2219)	0.959*** (0.0057)	0.344*** (0.0535)	0.731*** (0.1418)	0.748*** (0.2270)	0.718*** (0.2305)
Log (CCP_{t-1})	−0.001 (0.0028)	0.029 (0.0351)	0.254** (0.1150)	0.472** (0.2375)	0.472** (0.2241)					
CCP*HHC					0.010 (0.0727)					
Log ($CCPs_{t-1}$)						0.040*** (0.0118)	0.016 (0.0354)	0.659*** (0.2506)	0.825* (0.4931)	0.509* (0.3002)
CCPs*HHC										−0.031 (0.0709)
Log (MA_t)				−1.516** (0.7093)	−1.139 (0.8446)				−1.320 (0.9511)	0.053 (0.6329)
Log($15\text{-}29_t$)				0.095 (0.4010)	0.031 (0.4401)				0.270 (0.4177)	0.35 (0.3852)
Log($30\text{-}40_t$)				−2.193** (0.8870)	−2.432*** (0.7774)				−1.854* (0.9621)	−1.214* (0.7300)
Log (EMP_t)				−0.494 (1.2945)	−1.197 (1.2071)				−0.073 (1.4393)	−1.109* (0.6465)
Log (LTU_t)				0.207 (0.1874)	0.076 (0.1354)				0.151 (0.2041)	−0.033 (0.0853)
Log ($GDPn_t$)				−0.897*** (0.2780)	−0.927*** (0.2718)				−0.303 (0.2421)	−0.143 (0.1539)
Log ($GDPr_t$)				1.924*** (0.6270)	2.075*** (0.5631)				0.754 (0.6261)	0.578 (0.4517)
constant	0.213*** (0.0389)	4.157*** (0.3463)	1.431 (0.9437)	−8.432 (5.7439)	−11.910** (4.8658)	0.426*** (0.0708)	4.291*** (0.3864)	4.034** (1.6075)	2.149 (7.7736)	−3.482 (3.2180)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,632	1,632	1,632	1,261	1,261	1,632	1,632	1,632	1,261	1,261

(Continues)

TABLE 1 (Continued)

	(1) Pooled OLS	(2) Fixed effects	(3) Sys-2 GMM	(4) Sys-2 GMM	(5) Sys-2 GMM	(6) Pooled OLS	(7) Fixed effects	(8) Sys-2 GMM	(9) Sys-2 GMM	(10) Sys-2 GMM
Dependent variable is Log (HC_t)										
Regions	283	283	283	228	228	283	283	283	228	228
T-min		1.0	1.0	1.0	1.0		1.0	1.0	1.0	1.0
T-avg		5.8	5.8	5.5	5.5		5.8	5.8	5.5	5.5
T-max		6.0	6.0	6.0	6.0		6.0	6.0	6.0	6.0
AR(1)			[0.000]	[0.001]	[0.003]			[0.000]	[0.000]	[0.002]
AR(2)			[0.910]	[0.356]	[0.460]			[0.469]	[0.414]	[0.615]
Hansen J-Test			[0.115]	[0.474]	[0.599]			[0.563]	[0.304]	[0.071]
Diff-in-Hansen Test			[0.400]	[0.380]	[0.614]			[0.390]	[0.273]	[0.349]
Instruments			14	23	25			12	24	25
R2	0.973	0.961	0.887	0.847	0.821	0.973	0.967	0.913	0.871	0.923

Notes: *HC* and *HCter* are values of regional levels of human capital based on upper secondary and tertiary education, respectively. *CCP* and *CCPs* are values of the regional levels of employment in the cultural and creative sectors and the employment ratio of cultural and creative industries to the total number of employees, respectively. *15–29* is the regional density of young people between 15 and 29 years old. *30–40* is the regional density of individuals between 30 and 40 years old. *MA* is the regional median age. *EMP* is the regional employment rate of people with secondary and tertiary education. *LTU* is the regional long-term unemployment rate. *GDPn* is the regional gross domestic product at market prices. *GDPr* is the regional gross domestic product at purchasing power standard per inhabitant. *HHC* in interactions is for regions with high endowment of human capital. *Lag* before variables'" name is for lagged values. Construction of variables is reported in subsection 3.2. Base sample - taken from Eurostat – is a balanced panel spanning from 2014 to 2020 with data at one-year intervals. The dependent variable is HC_t from columns (1) to (10). Standard errors are in parentheses, p-values in brackets. Pooled OLS and Fixed Effects regressions use robust standard errors clustered by NUTS 2 regions. All GMM regressions use robust standard errors and the Windmeijer (2005) finite sample correction for cluster-robust standard errors. Columns (3) to (5) and (8) to (10) collapse the matrix of instruments (Roodman, 2009b). Columns (3), (4) and (5) treat *log* (CCP_{t-1}) as endogenous. Columns (8), (9) and (10) treat *log* ($CCPs_{t-1}$) as endogenous. In columns (4), (5), (9) and (10) the log density of 15–29 years old individuals (15_29_t), the log median age (MA_t), the log density of 30–40 years old individuals (30_40_t) are added as demographic controls and exogenous instruments. The log ratio of secondary and tertiary educated employment (EMP_t), the log $GDPr_t$ and the log $GDPn_t$ are added as socio-economic controls and treated as endogenous, while the log long term unemployment (LTU_t) is added as controls. In columns (5) and (10) an interaction term with our core variables is introduced i.e. respectively, CCP*HHC and CCPs*HHC.

*, **, *** denote significance at 10%, 5% and 1%, respectively. The row for the Hansen J-test reports the p-values for the null hypothesis of instrument validity. The values reported for the Diff-in-Hansen test are the *p*-values for the validity of the additional moment restriction necessary for system GMM. The values reported for AR(1) and AR(2) are the p-values for first and second order autocorrelated disturbances in the first differences equations.

Source: our elaboration on Eurostat (2021).

HC; and columns (6)–(10) re-estimate the previous specifications but including $CCPs_{t-1}$ as an alternative measure of CCP.[8]

The estimate of Log (CCP_{t-1}) in column (3) was positive and statistically significant (0.254). This suggests that a one percentage point increase in CCP_{t-1} is likely to increase HC_t by about 0.25 percentage points. In other words, if a region employing 1,500 cultural and creative workers (such as Abruzzo, Italy, in 2014) could increase the employment (CCP_t) by about 15 workers, its level of HC_{t+1} would probably increase by about 0.25 percentage points; thus, Abruzzo, where the level of HC_{2014} was 524.5, would observe an increase in HC of 1.31 percentage points, reaching a value of 525.8 (the potential HC_{2015}).

The level of the coefficient of CCP_{t-1} in column 4 is 0.472, meaning that an increase of one percentage point in CCP_{t-1} was likely to increase HC_t by about 0.5 percentage points. Following the previous example, in this specification, the level of HC in Abruzzo increased by 2.47 points in 2015. Some control variables provided statistically significant coefficients, such as MA_{it}, $30\text{-}40_{it}$, $GDPn_{it}$ and $GDPr_{it}$. The density of people between 30 and 40 years old ($30\text{–}40_{it}$) had a negative effect on HC_{it}, but $GDPn_{it}$ and $GDPr_{it}$ had opposite effects on HC_{it}. Unexpectedly, $GDPn_{it}$ negatively influenced the level of HC, but when considering $GDPr_{it}$, the findings indicated that *it* had a positive effect on HC.

Column (5) adds an interaction term between our core variable and a dummy variable built on different regional endowments of HC. The coefficient of CCP_{it-1} was positive and statistically significant, and estimates showed that a one percentage point increase in CCP_{it-1} resulted in an increase of about 0.47% in HC_{it}, but this did not change for regions with high and low levels of average endowments of HC because the coefficients of the interactions were not statistically significant. Unexpectedly, column (5) shows a negative effect of $GDPn_{it}$ on HC_{it}, meaning that, *ceteris paribus*, an increase in *GDPn* in a region was likely to reduce the level of HC. Instead, we detected a positive impact of $GDPr_{it}$ on HC_{it}, meaning that an increase in *per capita* GDP was likely to enhance the level of HC. Finally, the coefficient of $30\text{-}40_{it}$ presented a negative estimate, suggesting a negative impact of this variable on HC, as mentioned previously. The other control variables had no statistically significant coefficients.

The expectations of H1 were confirmed, whereas those of H2 were not. In fact, the findings suggest that the impact of CCP on HC is positive in regions with either high or low levels of HC, since no difference was detected between them. Accordingly, our results align with recent evidence of the positive role played by culture-related issues in HC (Crociata et al., 2020), but from a different perspective, based on the specific role of CCP. Recalling the previously discussed theoretical framework, it is possible that a positive influence of CCP on HC could operate through different channels (i.e., individual and collective). Considering the activation mechanisms, CCP agents might enhance levels of HC in the places where they operate, both directly, with their mindset focused on education and participation in training courses, and indirectly, by activating culturally driven spillover effects and place-based cumulative effects of CCP, thus stimulating the emergence of culturally and creatively fertile social milieus as the basis of new and increased HC.

Certainly, feedbacks and system-effects can also play a relevant role in explaining the influence of CCP on HC. For instance, bidirectional relationships exist between cultural and creative industries and growth in terms of GDP (Boix Domenech et al., 2021; Marco-Serrano et al., 2014). Thus, increasing wealth can be considered a driver of positive HC dynamics through the enlargement of the cultural and creative sectors. Our empirical analysis confirmed the presence of such effects.

However, a statistically insignificant estimate of the interaction term between the proxy of CCP and different regional levels of HC calls for further research, particularly regarding the relationship between CCP and HC at finer-grained levels (as also suggested by the maps provided in this paper) and, eventually (when data becomes available), to distinguish between different categories of CCP and different aspects of HC (e.g., the already mentioned local

[8]Coefficients obtained with POLS and FE assumed no endogeneity between our proxies for CCP and those for HC; thus, they were not appropriate methods for this study. However, they were still needed to ensure that the GMM models provided consistent estimates. In fact, the estimation of lagged dependent variables using the GMM technique can be consistent if it shows a value included between the coefficients of the lagged dependent variable obtained with POLS and FE regressions (Bond et al., 2001). In the present case, GMM regressions provided good estimations across all specifications.

TABLE 2 GMM regression results on HCter

	(1) Pooled OLS	(2) Fixed effects	(3) sys-2 GMM	(4) sys-2 GMM	(5) Sys-2 GMM	(6) Pooled OLS	(7) Fixed effects	(8) Sys-2 GMM	(9) Sys-2 GMM	(10) Sys-2 GMM
Dependent variable is Log ($HCter_t$)										
Log (HC_{t-1})	0.980*** 0.0051)	0.341*** (0.0530)	0.791*** (0.1436)	0.878*** (0.1879)	0.805*** (0.1540)	0.971*** (0.0055)	0.342*** (0.0530)	0.847*** (0.0905)	0.636*** (0.2005)	0.638*** (0.1925)
Log (CCP_{t-1})	−0.002 (0.0031)	0.029 (0.0391)	0.297** (0.1403)	0.776* (0.4136)	0.642** (0.2587)					
CCP*HHC					0.097 (0.0984)					
Log ($CCPs_{t-1}$)						0.031** (0.0133)	0.017 (0.0391)	0.592* (0.3423)	0.843* 0.4378)	0.769* (0.4467)
CCPs*HHC										−0.262 (0.2280)
Log (MA_t)				−2.780** (1.1126)	0.627 (1.1029)				−1.815* (1.0029)	−0.182 (1.7507)
Log($15\text{-}29_t$)				0.200 (0.5139)	−0.321 (0.6128)				0.428 (0.5792)	0.977 (0.7578)
Log($30\text{-}40_t$)				−2.764** (1.2718)	−2.175*** (0.7484)				−2.271** (0.9784)	−0.820 (1.6527)
Log (EMP_t)				0.352 (1.5240)	−4.248** (2.0410)				−0.225 (1.9356)	−0.566 (2.0507)
Log (LTU_t)				0.403 (0.2513)	−0.486* (0.2554)				0.178 (0.2423)	0.135 (0.2541)
Log ($GDPn_t$)				−0.855** (0.4220)	−0.978** (0.4542)				−0.228 (0.2286)	−0.251 (0.2169)
Log ($GDPr_t$)				1.884** (0.8618)	1.583* (0.8493)				1.027 (0.8605)	0.326 (1.0744)
constant	0.161*** (0.0352)	3.531*** (0.2942)	0.299 (0.5706)	−5.074 (7.0196)	−17.705** (8.6254)	0.311*** (0.0691)	3.670*** (0.3396)	2.921* (1.5798)	0.318 (9.1822)	4.418 (9.4548)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,632	1,632	1,632	1,261	1,261	1,632	1,632	1,632	1,261	1,261

TABLE 2 (Continued)

	(1) Pooled OLS	(2) Fixed effects	(3) sys-2 GMM	(4) sys-2 GMM	(5) Sys-2 GMM	(6) Pooled OLS	(7) Fixed effects	(8) Sys-2 GMM	(9) Sys-2 GMM	(10) Sys-2 GMM
Dependent variable is Log ($HCter_t$)										
Regions	283	283	283	228	228	283	283	283	228	228
T-min		1.0	1.0	1.0	1.0		1.0	1.0	1.0	1.0
T-avg		5.8	5.8	5.5	5.5		5.8	5.8	5.5	5.5
T-max		6.0	6.0	6.0	6.0		6.0	6.0	6.0	6.0
AR(1)			[0.000]	[0.000]	[0.000]			[0.000]	[0.001]	[0.000]
AR(2)			[0.253]	[0.114]	[0.215]			[0.182]	[0.303]	[0.356]
Hansen J-Test			[0.038]	[0.206]	[0.328]			[0.408]	[0.571]	[0.498]
Diff-in-Hansen Test			[0.549]	[0.065]	[0.251]			[0.251]	[0.753]	[0.848]
Instruments			14	23	25			12	24	24
R2	0.917	0.904	0.912	0.901	0.840	0.916	0.909	0.947	0.882	0.896

Notes: *HC* and *HCter* are values of regional levels of human capital based on upper secondary and tertiary education, respectively. *CCP* and *CCPs* are values of the regional levels of employment in the cultural and creative sectors and the employment ratio of cultural and creative industries to the total number of employees, respectively. *15–29* is the regional density of young people between 15 and 29 years old. *30–40* is the regional density of individuals between 30 and 40 years old. *MA* is the regional median age. *EMP* is the regional employment rate of people with secondary and tertiary education. *LTU* is the regional long-term unemployment rate. *GDPn* is the regional gross domestic product at market prices. *GDPr* is the regional gross domestic product at purchasing power standard per inhabitant. *HHC* in interactions is for regions with high endowment of human capital. *Lag* before variables'" name is for lagged values. Construction of variables is reported in subsection 3.2. Base sample—taken from Eurostat—is a balanced panel spanning from 2014 to 2020 with data at one-year intervals. The dependent variable is $HCter_t$ from columns (1) to (10). Standard errors are in parentheses, p-values in brackets. Pooled OLS and Fixed Effects regressions use robust standard errors clustered by NUTS 2 regions. All GMM regressions use robust standard errors and the Windmeijer (2005) finite sample correction for cluster-robust standard errors. Columns (3) to (5) and (8) to (10) collapse the matrix of instruments (Roodman, 2009b). Columns (3), (4) and (5) treat *log* (CCP_{t-1}) as endogenous. Columns (8), (9) and (10) treat *log* ($CCPs_{t-1}$) as endogenous. In columns (4), (5), (9) and (10) the log density of 15–29 years old individuals (15_29_t), the log median age (MA_t), the log density of 30–40 years old individuals (30_40_t) are added as demographic controls and exogenous instruments. The log ratio of secondary and tertiary educated employment (EMP_t), the log $GDPr_t$ and the log $GDPn_t$ are added as socio-economic controls and treated as endogenous, while the log long term unemployment (LTU_t) is added as controls. In columns (5) and (10) an interaction term with our core variable is introduced i.e. respectively, CCP*HHC and CCPs*HHC.

*, **, *** denote significance at 10%, 5% and 1%, respectively. The row for the Hansen J-test reports the p-values for the null hypothesis of instrument validity. The values reported for the Diff-in-Hansen test are the p-values for the validity of the additional moment restriction necessary for system GMM. The values reported for AR(1) and AR(2) are the p-values for first and second order autocorrelated disturbances in the first differences equations.

Source: our elaboration on Eurostat (2021).

presence of education structures and curricula, the various disciplines and fields of education, and the skill compositions of local productive specializations).

Columns (6)–(10) show the same specifications but employ a different proxy for CCP (i.e., $CCPs_{it\text{-}1}$—the employment ratio of cultural and creative industries to the total number of employees). As explained previously, we detected a positive impact of $CCPs_{it\text{-}1}$ on HC_{it}, and the interaction term between our proxy for CCP and regions highly endowed with HC resulted in a statistically insignificant estimate. Thus, H1 was confirmed, but H2 was not.[9]

Table 2 re-estimates the same specifications as shown in Table 1 but employs a different proxy for HC ($HCter_{it}$). These estimates confirm our findings, in general. Indeed, the coefficients in Table 2 of the core variables were slightly higher than those shown in Table 1, suggesting that the influence of CCP on HC was even stronger for the subsample of very highly educated people (i.e., individuals with a tertiary education). This may suggest the presence of a different effect of CCP on HC when assessing the quality of place relative to the endowment of HC.

5 | CONCLUSION

With the advent of a “cultural turn” in economics (Amin & Thrift, 2007) and policymaking (Nuccio & Ponzini, 2017), scholars have increased their research efforts to study the relationship between culture, creativity, and several socio-economic factors. In particular, some contributions have proved that cultural and creative industries can be important drivers of the evolution of knowledge-based economies (Power & Scott, 2004; Pratt, 2004; Scott, 2014).

Some investigations have focused on cultural participation or the demand side of culture (Crociata et al., 2020), but few researchers have investigated the role played by supply in the cultural and creative sectors. This paper contribute to filling this gap by elaborating on Cultural and Creative Production (CCP). Focusing on regional CCP allowed us to consider the supply of culture and creativity—precisely, the cultural and creative side that is likely to create, renovate, and eventually decrease the cultural and creative environment of a region—rather than exclusively considering cultural demand. Thus, we were able to consider the parts of cultural and creative content that might benefit local agents in the future or indirectly, simply because supply chains reach the places. Nowadays, this appears to be increasingly important in societies characterized by knowledge-based economies, where culture and creativity seemingly have increasing impacts on social progress, equity among people, and recovery strategies (OECD, 2021).

This work studied the role of CCP in fostering Human Capital (HC) as one of the main drivers of (regional) economic development across some NUTS 2-level European regions. Empirically, we examined data on cultural and creative employment as a relevant proxy for CCP. The available data allowed us to investigate both variations of the phenomena over time and over space. The results suggest that an increase in activities that generate cultural and creative content (i.e., CCP) positively affects HC at the regional level, whereas we detected no differences across regions endowed with different average levels of HC. A fertile cultural and creative environment driven by CCP and its associated knowledge spillovers may therefore lead to different but related consequences. In the conceptual section, we referred to various activation mechanisms or transmission channels that help explain such relationships. At an individual level, a well-endowed cultural and creative regional supply may lead individuals to activate cognitive mechanisms that sustain and improve their educational attainment through traditional education and lifelong learning. At a collective level, CCP may activate culture-driven regional path renewal and path diversification, thus re-modulating the educational attainment and composition of the workforce (HC). In general, finding such positive relationships contributes to advancing the existing knowledge about the impacts of regional variations in culture and creativity through new evidence-based research (Huggins et al., 2021).

Referring to an increasing number of culturally and creatively driven strategies for urban and regional development (Evans, 2002; Grodach, 2017), our findings suggest some policy implications. The endowment of HC is often

[9]The statistics included different GMM specifications: the Arellano and Bond test for autocorrelation (AR2), the Sargan–Hansen J test, and the difference-in-Hansen test. These tests ensured the robustness and reliability of our estimates across all the specifications.

market driven, and consequently, it is likely to be concentrated in high-performing regions. Policy measures aimed at preventing polarized dynamics that are detrimental to fair and convergent development could consider initiatives supporting education and lifelong learning but also introduce specific strategies for supporting for CCP in underdeveloped regions. Such strategies, with their positive impacts on the employment of local workforce, would also reduce the risk of overeducation related the first type of initiatives (Ramos et al., 2012).

Some limitations to this study remain. We were unable to directly investigate the role played by heterogeneity in CCP at different levels. Although data limitations prevented us from undertaking a direct investigation of different kinds of heterogeneities, we considered regional ones in the model by using regional fixed effects. However, we are aware of other sources of heterogeneity, such as different sectors of CCP, different market orientations, the different weights of large and small firms, internationalization specificities, and differences in labour forces. Their consideration, possibly within large-scale analyses or in-depth case studies, would surely provide a more detailed picture of the relationship between CCP and HC. Therefore, such aspects will require more research effort in the future. Finally, the availability of data for a longer time span could facilitate the direct observation of variations based on long-term activation mechanisms, providing interesting new research avenues for investigation in the future.

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APPENDIX I

TABLE A1 Summary statistics

		Mean	Std. Dev.	Min	Max	N/n/T-bar
HC	overall	852.90	651.43	36.2	3,443.58	2,241
	between		640.70	58.85	3,193.21	327
	within		101.94	255.88	1,323.23	6.85
HCter	overall	378.07	340.09	7.08	2,052.54	2,241
	between		336.21	10.58	1,815.94	327
	within		51.54	81.23	650.9	6.85
lag_HC	overall	868.89	656.27	43.44	3,443.58	1,957
	between		651.69	58.94	3,220.39	327
	within		85.80	453.92	1,306.17	5.98
lag_HCter	overall	383.46	341.36	7.62	2,052.54	1,957
	between		338.38	11.03	1,812.07	327
	within		48.15	156.89	651.38	5.98
CCP	overall	30,255	35.24	1.4	374	1,906
	between		34.78	1.62	338.06	283
	within		3.30	−9.60	66.2	6.73
CCPs	overall	.035	.017	.004	.155	1,906
	between		.016	.008	.125	283
	within		.003	.018	.065	6.73
15_29	overall	.18	.028	.11	.31	2,235
	between		.028	.12	.31	327
	within		.005	.15	.20	6.83
30_40	overall	.13	.019	.09	.22	2,235
	between		.019	.09	.22	327
	within		.005	.11	.15	6.83
MA	overall	41.96	4.74	20	52	2,235
	between		4.68	20.98	51.24	327
	within		.60	39.445	44.36	6.83
EMP	overall	.66	.099	.279	.866	2,248
	between		.097	.306	.842	327
	within		.019	.578	.723	6.87
LTU	overall	.040	.041	.003	.233	2,056
	between		.038	.004	.195	321
	within		.014	−.021	.106	6.40
GDPn	overall	51,613.73	65,723.72	1,168.64	758,527.3	1,914
	between		65,476.43	1,330.43	702,138.1	276
	within		5,162.503	−7,473.50	108,002.9	6.93

(Continues)

TABLE A1 (Continued)

		Mean	Std. Dev.	Min	Max	N/n/T-bar
GDPr	overall	26,783.75	11,386.76	6,700	81,300	1,914
	between		11,364.48	7,414.28	78,228.57	276
	within		1,784.28	−3,173.39	44,326.61	6.93

Notes: See note to Table 1 for variables'' definitions. Their construction is reported in ubssection 3.2. The levels "between" and "within" represent the decomposition of the variability of our variables. The within level represents intra-regional variability while the between level represents the inter-regional one which embodies the permanent and stable differences among observations. N represents observations'' count, *n* the number of regions taken into account and T-bar is the mean number of the available period.

Source: our elaboration on Eurostat (2021).

TABLE A2 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Log (HC)	1.000												
(2) l. Log (HC)	0.982 (0.000)	1.000											
(3) Log (HCter)	0.962 (0.000)	0.942 (0.000)	1.000										
(4) l. Log (HCter)	0.950 (0.000)	0.961 (0.000)	0.986 (0.000)	1.000									
(5) Log (CCP)	0.354 (0.000)	0.359 (0.000)	0.375 (0.000)	0.381 (0.000)	1.000								
(6) Log (CCPs)	0.621 (0.000)	0.627 (0.000)	0.654 (0.000)	0.663 (0.000)	0.621 (0.000)	1.000							
(7) Log (15_29)	−0.148 (0.000)	−0.146 (0.000)	−0.054 (0.000)	−0.051 (0.000)	0.013 (0.000)	−0.132 (0.000)	1.000						
(8) Log (30_40)	−0.326 (0.000)	−0.316 (0.000)	−0.237 (0.000)	−0.228 (0.000)	0.238 (0.000)	0.181 (0.000)	0.339 (0.000)	1.000					
(9) Log (MA)	0.300 (0.000)	0.298 (0.000)	0.166	0.164 (0.000)	0.015 (0.000)	0.197 (0.000)	−0.846 (0.000)	−0.509 (0.000)	1.000				
(10) Log (EMP)	0.652 (0.000)	0.653 (0.000)	0.565 (0.000)	0.564 (0.000)	0.322 (0.000)	0.528 (0.000)	−0.307 (0.000)	−0.226 (0.000)	0.493 (0.000)	1.000			
(11) Log (LTU)	−0.347 (0.000)	−0.360 (0.000)	−0.312 (0.000)	−0.317 (0.000)	−0.288 (0.000)	−0.251	−0.174 (0.000)	0.038 (0.86)	0.027 (0.229)	−0.687 (0.000)	1.000		
(12) Log (GDPn)	0.481 (0.000)	0.483 (0.000)	0.475 (0.000)	0.476	0.884 (0.000)	0.520 (0.000)	−0.146 (0.000)	−0.069 (0.000)	0.212 (0.000)	0.376 (0.000)	−0.283 (0.000)	1.000	
(13) Log (GDPr)	0.725 (0.000)	0.723 (0.000)	0.716 (0.000)	0.715 (0.000)	0.507 (0.000)	0.752 (0.000)	−0.274 (0.000)	−0.134 (0.000)	0.391 (0.000)	0.670 (0.000)	−0.374 (0.000)	0.643 (0.000)	1.000

Notes: See note to Table 1 for variables'" definitions. Their construction is reported in subsection 3.2. The level of statistical significance is reported within parentheses.
Source: our elaboration on Eurostat (2021).

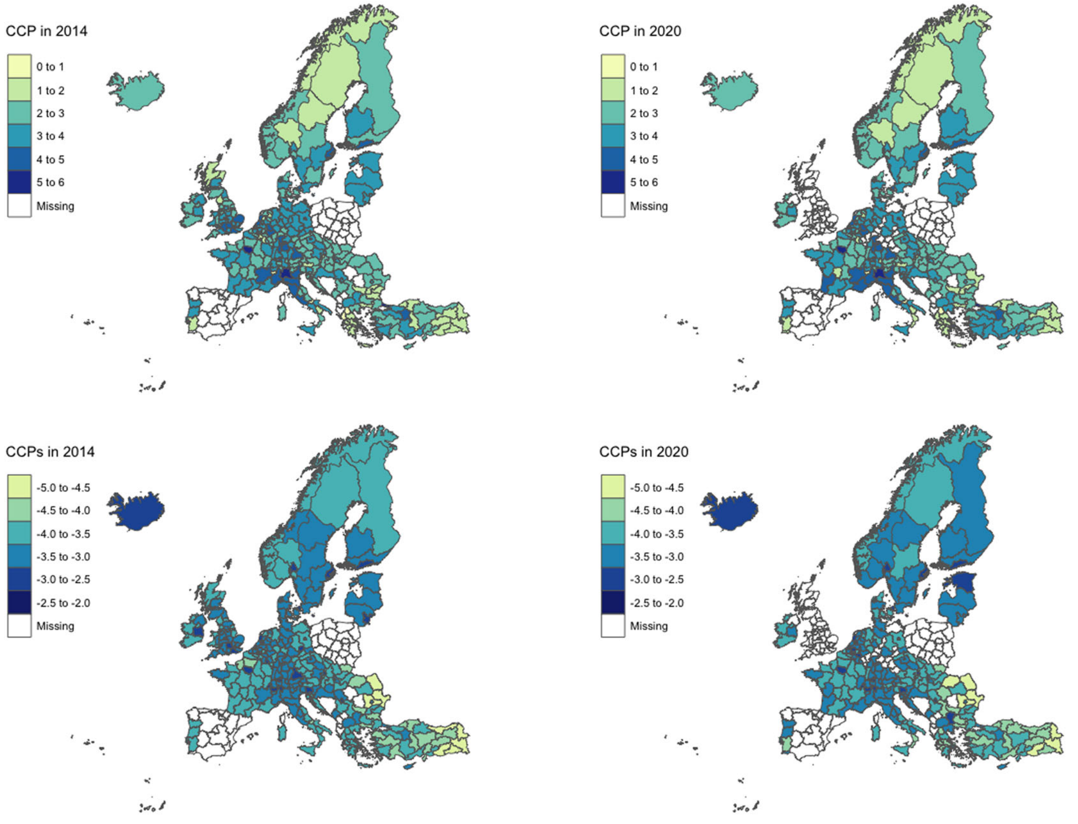

FIGURE A1 Cultural and creative production (CCP-CCPs) across European regions in 2014 and in 2020. *Notes*: See note below Figure 1 for variables'" definitions. Their construction is reported in subsection 3.2. *Source*: our elaboration on Eurostat (2021).

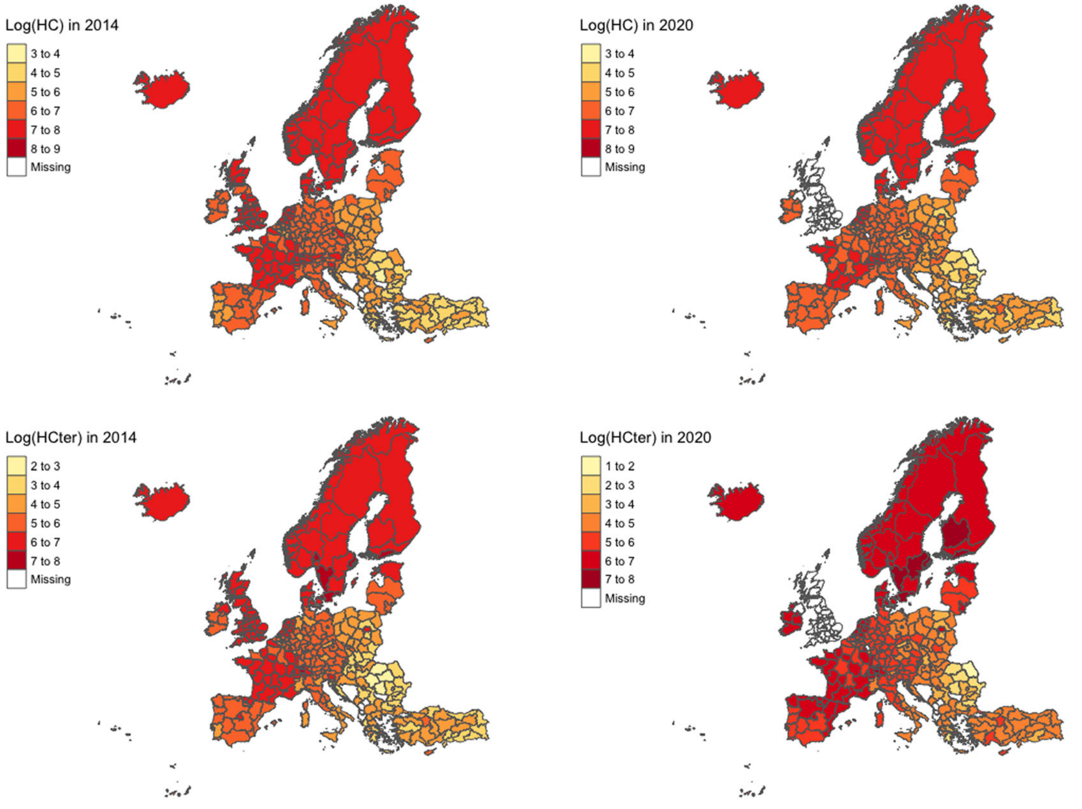

FIGURE A2 *HC* across European regions in 2014 and in 2020. *Notes*: See note below Figure 1 for variables'" definitions. Their construction is reported in subsection 3.2. *Source*: our elaboration on Eurostat (2021).

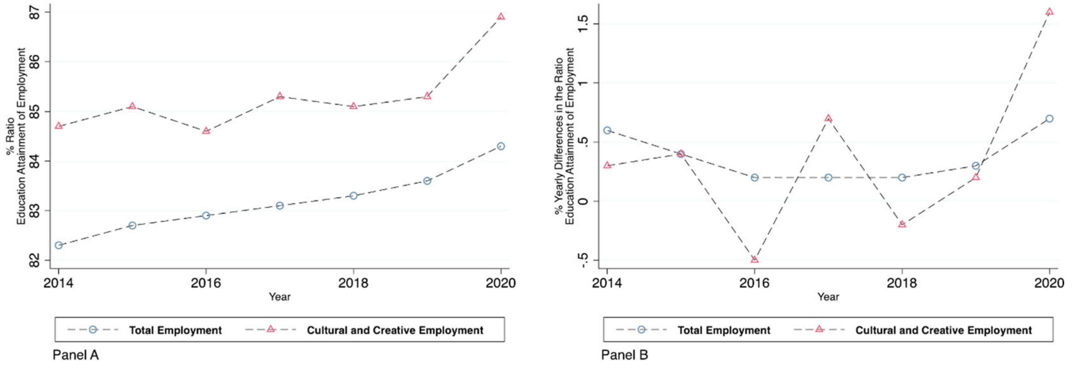

FIGURE A3 Ratio and yearly differences in the ratio of upper-secondary educated workers in cultural and creative employment and total employment, 2014–2020. *Notes*: The dashed line with red triangles represents the ratio of upper-secondary educated workers in the employment of cultural and creative sectors (ISCED, 2011; ED3–8), and the dashed line with blue circles represents the ratio of upper-secondary educated workers in the total economy in Panel A. The dashed line with red triangles represents yearly differences in the ratio of upper-secondary educated workers in the employment of cultural and creative sectors, and the dashed line with blue triangles represents yearly differences in the ratio of upper-secondary educated workers in the total economy in Panel B. *Source*: our elaboration on Eurostat (2021).