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FULL ARTICLE

Cultural and creative industries and regional diversification: Does size matter?

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Abstract

This paper aims at analysing how the presence of workers employed in cultural and creative industries (CCIs) is related to regional specialized diversification. From a theoretical perspective, CCIs drive economic development and local innovative capacity by facilitating processes of cross-fertilization of ideas. This study estimates an entry model analysing the ability of Italian provinces to successfully create new sectoral specializations. The results indicate that the relationship between the share of employees in CCIs and the probability of creating new sectoral specializations is non-linear, highlighting the need for CCIs-led policies to achieve a certain level of critical mass to be successful.

KEYWORDS

creative and cultural economy, diversity, employment growth, specialized diversification

JEL CLASSIFICATION

R11; O10

1 | INTRODUCTION

Over the last two decades the advocacy for culture-creativity based approach to development has been recognized by many scholars (Florida, 2002; Howkins, 2001; Pratt, 2004; Throsby, 2001 among others) and international institutions (European Commission, 2010, 2012; UNCTAD, 2008, 2010; UNESCO, 2013). Consequently, a growing body of contributes has acknowledged the potential of the Cultural and Creative Industries (CCIs) for growth, as compared to other sectors of the economy.

At the European level, the Regulation (EU) No 1295/2013 establishing the Creative Europe Programme (2014 to 2020) sustains the competitiveness of the European cultural and creative sectors with a view to promoting smart, sustainable and inclusive growth even at regional and local levels.

The issue of culture-led development has therefore gained attention at the regional level. More specifically, since the production and consumption of cultural goods tends to be place-specific (Santagata, 2002; Scott, 2000; Storper & Scott, 2009), it contributes to partially explaining local divergences in economic growth patterns. Theoretical discourses and empirical evidences suggest that the multifaceted nature of cultural and creative workers contributes in different ways to long-term regional economic performance (Boix, Capone, De Propris, Lazzeretti, & Sanchez, 2016; Boix-Domenech & Soler-Marco, 2017; Crociata, Agovino, Russo, & Quaglieri Domínguez, 2018; Power & Scott, 2004; Pratt, 2004). However, fully deploying cultural and creative skills as a developmental driver for local economies is often problematic (Cerisola, 2018) and calls for an adequate regulatory framework (Sacco & Crociata, 2013).

The regional studies literature links the positive relationship between CCIs and local development to the positive role played by diversity *à la* Jacobs (1969). Indeed, the rationale behind the linkages between CCIs and regional diversification is based on the assumption that the interaction among different types of creative talents favours local economic development (Cerisola, 2018). More specifically, the diversity of the workforce in a local system is also expressed at the individual level and increases the regional capacity to absorb new ideas and turn them into new entrepreneurial opportunities (Piergiovanni, Carree, & Santarelli, 2012). The mechanisms through which CCIs potentially affect regional diversity rely on the creativity, skills and talent characterizing these sectors, which could be innovatively used as inputs in the production processes of other sectors (Bakhshi, McVittie, & Simmie, 2008; Lazzeretti, Innocenti, & Capone, 2017). Hence, CCIs are seen as a cross-sectional industry stimulating growth in a variety of other sectors by providing creative inputs in various local production processes. Indeed, according to Bakhshi et al. (2008) the impacts of CCIs on the wider economy arise through the activation of cross-fertilization processes via knowledge spillovers among different sectors.

Hence, from a theoretical perspective, in the last decade there has been a growing interest in the relationship between the cultural and creative sectors and economic development, focusing on the role of CCIs as key driver fostering the creative economy and encouraging cross-sectoral cooperation by means of cultural and creative spillovers. Despite the growing interest on this topic, only few empirical studies have focused on CCIs and diversification, building on the recently established approach based on related variety (Boschma & Frenken, 2011; Frenken, Van Oort, & Verburg, 2007; Lazzeretti et al., 2017).

This paper sits somewhere on the crossroads between the traditional economic approach on diversification as the most important driver for regional economic growth (as in Frenken et al., 2007; McCann, 2013; Cortinovis, Xiao, Boschma, & Van Oort, 2017) and the new stream of research investigating the effects of CCIs in fostering innovation and growth in the wider economy (Bakhshi et al., 2008). More specifically, the aim of this study is to contribute to the literature by analysing how the presence of workers employed in CCIs in the local economy is related to regional specialized diversification.[1] In particular, based on the findings of the existing literature on CCIs, this analysis seeks to answer the following research question:**RQ** To what extent is the presence of workers employed in cultural and creative industries (CCIs) related to regional specialized diversification?

To answer the research question this study empirically analyses the ability of Italian provinces to successfully build up a specialization in new sectors in the period 2012–16. The results indicate that, above a certain threshold, the relationship between the presence of workers in CCIs and the ability of Italian provinces to successfully create new sectoral specializations is positive. More specifically, these findings highlight that this relationship is not linear, rather is quadratic. The implications of these results indicate that there is a need for CCIs-led policy to achieve a certain level of critical mass to generate positive spillovers allowing the local economy to increase its specialized

[1]The concept of "specialized diversity" refers to the diversification of an economy in terms of the variety of sectors this economy is specialized in. Following McCann and Ortega-Argilés (2015), economic growth is not enhanced by diversification *per se*, rather, what really matter are the patterns of specialized diversification across related sectors.

diversification. Hence, the contribution of this paper to the literature is twofold: these findings expand the empirical literature focused on the drivers of regional diversification, and they also enrich the literature on CCIs-led policies for regional development.

The rest of the paper is structured as follows. Section 2 presents a review of the relevant literature. Section 3 describes the econometric approach, as well as the data and variables used in the analysis. Section 4 discusses the main results and Section 5 concludes.

2 | LITERATURE BACKGROUND

Regional science has increasingly become a suitable discipline to understand in details the different channels through which CCIs impact on long-run growth trajectories (Boix et al., 2016; Cerisola, 2018; Crociata et al., 2018; Piergiovanni et al., 2012). In particular, CCIs are more and more acknowledged as a new important driver of economic development and growth, as well as a key factor enhancing innovation and the creation of new firms (Jeffcutt & Pratt, 2009). For instance, Cerisola (2018) and Piergiovanni et al. (2012) have empirically studied the effects of different creative components on employment dynamics and added value creation in Italian provinces. Both studies show the existence of a positive relationship between local growth and the presence of CCIs.

According to Chapain, Cooke, De Propris, MacNeill, and Mateos-Garcia (2010), the local presence of workers in CCIs generates a stimulating environment characterized by high levels of exchange of ideas and opinion, which, in turn, reinforce innovation processes and the diffusion of knowledge in the region. This is due to the strong knowledge base characterizing CCIs (Martin & Moodysson, 2011), whose creation appears to be highly context specific and grounded in localized communities of interactions (Brandellero & Kloosterman, 2010; Cohendet, Grandadam, Simon, & Capdevila, 2014; Lena, 2012; Martin & Moodysson, 2011). Accordingly, Morrison (2008) indicated that small epistemic communities capitalize creativity and diversity in the form of networks of heterogeneous agents concentrating knowledge and making some regions more dynamic than others. Moreover, such regional milieus of agents have positive impacts on entrepreneurship (Audretsch, Dohse, & Niebuhr, 2010) and local diversity, by increasing the regional capacity to absorb new ideas and turn them into entrepreneurial opportunities (Jeffcutt & Pratt, 2009). Similarly, Lazzeretti (2012) highlighted how CCIs contribute to stimulate local innovation processes by facilitating and promoting intersectoral linkages between creative industries and the other sectors. Moreover, Innocenti and Lazzeretti (2019) showed how CCIs require the presence of other related sectors to generate intersectoral connections and promote the exchange of knowledge and ideas among different sectors.

Knowledge exchanges and variety could facilitate the transfer of ideas between creative businesses and firms in other industries also considering the supply chain framework (Bakhshi & McVittie, 2009). Indeed, CCIs products or services may be direct inputs of production processes in other local industries. Hence, supply chain linkages provide creative inputs to other sectors and facilitate the transfer of ideas and knowledge originating from CCIs, leading to start-up creation and new business formation, (Bakhshi et al., 2008). Overall, there is increasing evidence highlighting the key role played by CCIs in enhancing economic growth and regional development, due to their capacity to foster cross-fertilization processes and transversal innovations in the local economy (Bakhshi et al., 2008; Lazzeretti, et al., 2017; Piergiovanni et al., 2012; Stam, De Jong, & Marlet, 2008). More specifically, the high degree of variety characterizing CCIs is a key factor enabling them to efficiently interact with the other sectors, enhancing local innovation and economic growth (Higgs, Cunningham, & Bakhshi, 2008).

Among the key drivers facilitating the direct transfer and diffusion of knowledge (in general, and specifically for CCIs), the literature highlights the processes of labour pooling and labour mobility (Duranton & Puga, 2004; Malberg, 2003). Indeed, the mobility of skilled workers represents an important vehicle matching labour supply and labour demand, and making knowledge circulate both among regions (Iammarino & McCann, 2006; Malberg & Power, 2005; Ottaviano & Peri, 2006) and among countries (Rodriguez-Pose & Vilalta-Bufi, 2005; Saxenian & Sabel, 2008). However, labour mobility is not *per se* a sufficient condition for ensuring regional growth, since an effective matching of skills is needed to give rise to knowledge spillovers and learning across industries (Boschma, Eriksson, & Lindgren, 2009) and production complementarities (Duranton & Puga, 2004). Indeed, workers are more likely to change between related industries where they can use their skills more, creating even more opportunities for new firms to locate there. Following Frenken et al. (2007), who argued that inter-industry knowledge spillovers are expected to primarily occur among sectors embedding a certain degree of cognitive proximity, Boschma et al. (2009) found evidence that only labour flows between skill-related industries positively impact on regional (productivity) growth.

Consequently, the idea that sector diversification and cultural relatedness can be an important driver of economic development is also associated to the relatedness approach (Boschma & Iammarino, 2009; Frenken et al., 2007; Hidalgo & Hausmann, 2009; Hidalgo, Klinger, Barabási, & Hausmann, 2007)) and the more specific concept of skill-relatedness (Neffke & Svensson-Henning, 2008[2]). According to this view, successful economic development entails a process of gradual diversification of the production structure. This is driven by technological and cognitive linkages between the existing local economic structure and the yet unused local potential of similar economic activities. Hence, relatedness—and in particular CCIs' relatedness—is seen as a key lever for regional knowledge spillovers and learning opportunities because it maximizes the potential for growth of existing industries as well as the local sources of growth for new industries (Boschma et al., 2014).

3 | ECONOMETRIC STRATEGY, DATA AND VARIABLES

In order to identify how the presence of workers employed in CCIs in the local economy is related to regional specialized diversification (McCann & Ortega-Argilés, 2015), the analysis follows previous empirical studies (Boschma, Minondo, & Navarro, 2012; Cortinovis et al., 2017; Hidalgo et al., 2007) and estimates an entry model analysing the ability of Italian provinces[3] to successfully build up a specialization in a sector which is new for the province. Hence, the dependent variable is $\mathbf{NEW^{-}\ SPEC}_{s,p,t+5}$, a binary variable taking value 1 when province p builds up a specialization in sector s at time t+5[4], 0 otherwise. To specifically focus on the spillovers potentially generated by CCIs, the analysis only considers the creation of new specializations in sectors related to CCIs, which have been identified following the related variety literature (Frenken et al., 2007).[5] Additionally, to properly capture specialized diversification dynamics, the study only considers combinations of CCIs-related sectors and provinces such that at time t province p was not specialized in sector s. To detect whether a province is specialized in a sector, the analysis is based on the location quotient of each industry in each province, defined as:

$$LQ_{s,p} = \frac{\frac{E_{s,p}}{\sum_{s} E_{s,p}}}{\frac{\sum_{p} E_{s,p}}{\sum_{s,p} E_{s,p}}},$$

where $E_{s,p}$, refers to the number of workers employed in sector s in province p. Higher values of the location quotient indicate higher levels of specialization of sector s in province p relative to the overall specialization of that sector in all provinces. The study considers as specializations those combinations of sectors and provinces with a location quotient above 1.

[2]Neffke and Svensson-Henning (2008) argued that a more intense intersectoral labour mobility may indicate a more effective matching of skills and therefore a higher degree of skill-relatedness.

[3]Corresponding to NUTS 3 level of geographical definition.

[4]Following Cortinovis et al. (2017), the analysis considers 5-year intervals as a reasonable minimum length allowing capturing specialized diversification dynamics.

[5]In particular, this study considers as CCIs-related sectors those four-digit sectors (according to the NACE Rev. 2 code classification) belonging to the same two-digit class containing at least one cultural and creative sector.

The main independent variable included in the analysis is the share of workers employed in CCIs as a percentage of the total number of workers employed in each province (**EMPL_CCI**). Given the multi-dimensional nature of culture, the main challenge related to this point is to find an appropriate definition of sectors belonging to the group of CCIs. Indeed, both academic and institutional approaches (among others) have tried to define and fix the boundaries of CCIs sectors.

In order to overcome the debate concerning the CCIs taxonomy and measurement, this study considers an industry-based approach following the most recent definition proposed in the Guide to Eurostat Culture Statistics (2018), which classifies as cultural and creative sectors the ones listed in Table A.1 in Appendix A (according to the NACE Rev. 2 code classification at the four-digit level).

The main motivation supporting this approach is based on the fact that various political processes supporting CCIs in Europe are based on this definition. The implication is that this approach facilitates comparisons over time, between policies, countries and regions, social groups and industries, and contributes to increased transparency and accountability.

Following the literature on agglomeration spillovers, the analysis considers the possibility of non-linear interactions between the share of workers employed in cultural and creative industries and the ability of a province to build up a new specialization, and allows for linear and quadratic effects of the variable EMPL_CCI.

In order to better identify the relationship between CCIs and new sectoral specializations, this analysis considers as additional explanatory variable the relatedness of each sector with the rest of the local economy. This index captures the cognitive proximity between each sector and the existing structure of the local economy (Boschma, 2017; Hausmann & Klinger, 2006; Hidalgo & Hausmann, 2009; Hidalgo et al., 2007)[6]. Including this variable in the analysis allows isolating how the current structure of the economy favours the development of new technologies across related domains and, therefore, better identifying the linkages between the presence of workers employed in CCIs and regional specialized diversification.

Another relevant explanatory variable of the model is the local economic complexity. More specifically, the Economic Complexity Index (ECI) measures the diversity and sophistication of the productive structure of a country (or region) and reflects the emerging combination of the multiplicity of knowledge embedded in it (Hausmann et al., 2014; Hidalgo & Hausmann, 2009).[7] Products differ in the variety of capabilities they require, and countries (or regions) differ in the variety of capabilities that are available in their territories. Consequently, economies with more capabilities will be more diversified, and products requiring more capabilities will be accessible to fewer economies, and hence will be less ubiquitous. Measures of complexity—Economic Complexity Index (ECI) and Product Complexity Index (PCI)—combine information about the ubiquity of products and the diversification of places in order to capture information about the set of embedded capabilities. Given that intersectoral *cross-fertilization processes* are deeply influenced by the amount of knowledge embedded in the existing productive structure of an economy, the inclusion of this variable allows better distinguishing between the relationship of the general complexity of the local economy on the development of new sectoral specializations and the specific cross-fertilization processes driven by the multifaced structure of CCIs.

All the variables explained in the previous part of this section are computed using employment data provided by the Italian National Institute of Statistics (ISTAT), consisting of information about the yearly number of employees in each four-digit level sector in each Italian province for the years 2012–16.

To avoid problems of omitted-variable bias, which could cause issues of identification, the analysis also considers a number of control variables at the provincial level. To avoid problems of reverse causality, these control variables are all considered for the year 2012, that is, before the beginning of the considered specialization processes. More specifically, to control for the level of prosperity of the local economy, the provincial per capita annual gross domestic product (GDP *per capita*) is considered (as in Cortinovis et al., 2017). This information is derived from the

[6]See appendix B for additional details.

[7]Appendix C provides additional technical details.

TABLE 1 Descriptive statistics

	Mean	Std. Dev.	Min.	Max.
NEW_SPEC	0.10	0.30	0	1
EMPL_CCI	0.021	0.005	0.004	0.049
EMPL⁻ CCI^2	0.0005	0.0002	0.0000	0.0024
RELATEDNESS	0.30	0.07	0.11	0.55
COMPLEXITY	0.21	1.00	−1.49	2.03
EMPL_TOT	165,206	213,744	18,377	1,670,296
GDP (*PER CAPITA*)	25,188	5′,975	14,558	44,895
EDUCATION (in %)	0.36	0.06	0.16	0.49
R&D (in %)	0.11	0.08	0.02	0.41
POP DENSITY	246.5	303.6	37.3	2,590.7
ΔSPECIALIZATIONS	−0.005	0.063	−0.235	0.242
W_EMPL_CCI	0.022	0.002	0.016	0.029
W_EMPL⁻ CCI^2	0.0005	0.0001	0.0002	0.0009
W_RELATEDNESS	0.32	0.05	0.11	0.53
W_EMPL_TOT	191,038	118,441	30,579	573,870
W_R&D	0.12	0.04	0.05	0.25

Note: 4,675; 103 provinces; 73 sectors.

OECD regional database, available from 2001 to 2014. Additionally, the total number of employees in each province (**EMPL_TOT**) is also taken into account. This information is provided by ISTAT. In order to control for the local level of human capital, the analysis also includes the variable **EDUCATION** (see Crociata, Odoardi, Agovino, & Sacco, 2020), computed as the share of the provincial population with a higher education[8] (Moretti, 2004; Rauch, 1993). This information has been provided by the Italian Ministry of Education, University and Research (MIUR) statistical section, collected with respect to the location of Universities.

Moreover, the study controls also for the local level of research and development activities (**R&D**), defined as the level of provincial R&D employment[9] divided by the total employment of each province and provided by ISTAT (Cicerone, McCann, & Venhorst, 2020). To capture urbanization economies the analysis also considers the population density of each province (Mantegazzi, McCann, & Venhorst, 2020; Paci & Usai, 2008), measured as the number of inhabitants per squared kilometre (POP DENSITY), as derived from the OECD Regional Demographic Statistics. Given the relative nature of the dependent variable, the analysis controls for the change in the number of specialized sectors in each province (ΔSPECIALIZATION). This allows controlling for the fact that the creation of a new sectoral specialization might be the result of a shift in specialization, rather than an increase in local diversity. Finally, to account for possible agglomeration effects and spatial spillovers, the analysis considers a local spillover model (spatial lag of X model).[10] In particular, this study considered a spatial weight matrix (W) based on the queen contiguity between each province in Italy. Following the spatial econometric literature (Anselin, 1988; LeSage & Pace, 2009), the W matrix was standardized, such that each row sums to unity.

[8]Defined as a bachelor's degree or master's degree.

[9]A more suitable measure for R&D inputs is the total R&D expenditure per capita. Unfortunately, however, R&D expenditure data disaggregated at the level of the Italian provinces (NUTS 3) do not exist. They are only reported at the much larger spatial units of the broader Italian regions (NUTS 2) (Cicerone et al., 2020).

[10]Given the high multicollinearity related to the spatial lag of the variables COMPLEXITY, GDP, EDUCATION and POP DENSITY emerging from the Variance Inflation Factor (Kutner, Nachtsheim, & Neter, 2004), these variables have not been included in the regression estimation.

Table 1 reports the descriptive statistics of the variable capturing the rise of new specializations in CCIs-related sectors, as well as those relative to the explanatory variables at the provincial level which have been described above.[11]

Formally, it is possible to express as follows the model that is considered in this analysis:

$$\begin{aligned}\overline{\mathrm{NEWSPEC}}_{p,s,t+5} = {} & \beta_0 + \beta_1 \mathrm{EMPL}_{\mathrm{CCI}_{p,t}} + \beta_2 \mathrm{EMPL}_{\mathrm{CCI}_{p,t}}{}^2 + \beta_3 \mathrm{RELATEDNESS}_{p,s,t} \\ & + \beta_4 \mathrm{COMPLEXITY}_{p,t} + \beta_5 \mathrm{GDP}_{p,t} + \beta_6 \mathrm{EMPL}_{\mathrm{TOT}_{p,t}} + \beta_7 \mathrm{EDUCATION}_{p,t} \\ & + \beta_8 \mathrm{R\&D}_{p,t} + \beta_9 \mathrm{POP\,DENSITY}_{p,t} + \beta_{10} \Delta \mathrm{SPECIALIZATION}_{p,t} \\ & + \beta_{11} \sum_k w_{p,k} \mathrm{EMPL}_{\mathrm{CCI}_{k,t}} + \beta_{12} \sum_k w_{p,k} \mathrm{EMPL}_{\mathrm{CCI}_{k,t}}{}^2 \\ & + \beta_{13} \sum_k w_{p,k} \mathrm{RELATEDNESS}_{k,s,t} + \beta_{14} \sum_k w_{p,k} \mathrm{EMPL}_{\mathrm{TOT}\,k,t} \\ & + \beta_{15} \sum_k w_{p,k} \mathrm{R\&D}_{k,t} + \mu_s + \mu_r + \epsilon_{p,s,t},\end{aligned}$$

where $w_{p,k}$ is the contiguity-based spatial weight between province p and province k, μ_s and μ_r control for sectoral and regional (NUTS 2) fixed effects, respectively, and $\epsilon_{p,s,t}$ represents the clustered error term.

The model is estimated using a logit specification with clustered standard errors. In order to facilitate the interpretation of the results all the independent variables have been standardized before estimating the model.

4 | RESULTS

The analysis investigates whether and how the presence of workers employed in CCIs of the local economy is linked to regional specialized diversification, via the creation of new specializations in CCIs-related sectors. Table 2 shows the results of our empirical approach.

The first column of Table 2 (model (1)) shows the estimation results when only the share of employees of CCIs at the provincial level is considered. The second column of Table 2 (model (2)) reports the results when all the control variables are included, except for the spatial lags. Finally, the last column of Table 2 (model (3)) presents the results of the full model. This is the preferred specification and the rest of the discussion is based on this model.

First of all, with reference to the share of employees of CCIs at the provincial level, all the models estimate both linear and quadratic linkages and the results always indicate that the relationship between the provincial share of employees in CCIs at time t and the probability of creating a new sectoral specialization in CCIs-related sectors in the following five years is significant and not linear. More specifically, we find that the estimate for the linear relationship is significantly negative,[12] while the estimate for the quadratic interaction is significantly positive. This implies that the relationship between the share of employees in CCIs and the probability of creating a new sectoral specialization is stronger for higher values of the share of employees in CCIs.

As shown in Figure 1, this result can be graphically represented by plotting the average marginal effects of the provincial share of employees of CCIs on the probability of building up a new specialization in a sector related to CCIs.

The graph clearly shows that the ability of Italian provinces to successfully build up a specialization in a CCIs-related sector which is new for the local economy is not linearly related to the provincial share of employees in CCIs. Indeed, by simultaneously considering the linear and quadratic linkages, the results indicate that the average marginal effect of the local share of CCIs employees is significantly higher in provinces with larger shares of employees in CCIs. More specifically, the average marginal effect is positive when the local share of employees in

[11] Appendix D presents the correlation matrix between all the explanatory variables.

[12] In order to properly interpret the relationship between the presence of workers employed in CCIs and the ability of a province to build up a new sectoral specialization, it is important to simultaneously consider the linear relationship together with the quadratic one. Consequently (and as shown in Figure 1), the overall relationship is negative only with a considerably small presence of CCIs in the local economy.

TABLE 2 Entry model on the development of new CCIs-related sectoral specialization in Italian provinces

	Model (1) only CCI	Model (2) no spatial lags	Model (3) full model
EMPL_CCI	−0.3717*** (0.1368)	−0.9430*** (0.1425)	−0.7723*** (0.1512)
EMPL_ CCI^2	0.2511* (0.1497)	1.1218*** (0.1840)	1.0544*** (0.1854)
RELATEDNESS		0.6293*** (0.0881)	0.6267*** (0.1006)
COMPLEXITY		0.0043 (0.1443)	0.0558 (0.1690)
EMPL_TOT		−0.4422*** (0.1413)	−0.5070*** (0.1549)
GDP (*PER CAPITA*)		−0.2510 (0.1543)	−0.2884* (0.1663)
EDUCATION		0.0594 (0.1201)	0.0692 (0.1089)
R&D		0.0413 (0.0549)	0.0376 (0.0639)
POP DENSITY		0.0566 (0.0865)	0.0190 (0.0829)
ΔSPECIALIZATIONS		0.2396*** (0.0607)	0.2329*** (0.0644)
CONSTANT	−2.1934*** (0.0601)	−3.3523*** (0.7933)	−3.3747*** (0.8459)
Region fixed effects	No	Yes	Yes
Sector fixed effects	No	Yes	Yes
Spatial Lag of X (SLX)	No	No	Yes
AIC	3058.7	2869.5	2868.8
BIC	3078.1	3527.4	3558.9
Log Likelihood	−1526.4	−1332.7	−1327.4
Observations	4,675	4,675	4,675

Notes: Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

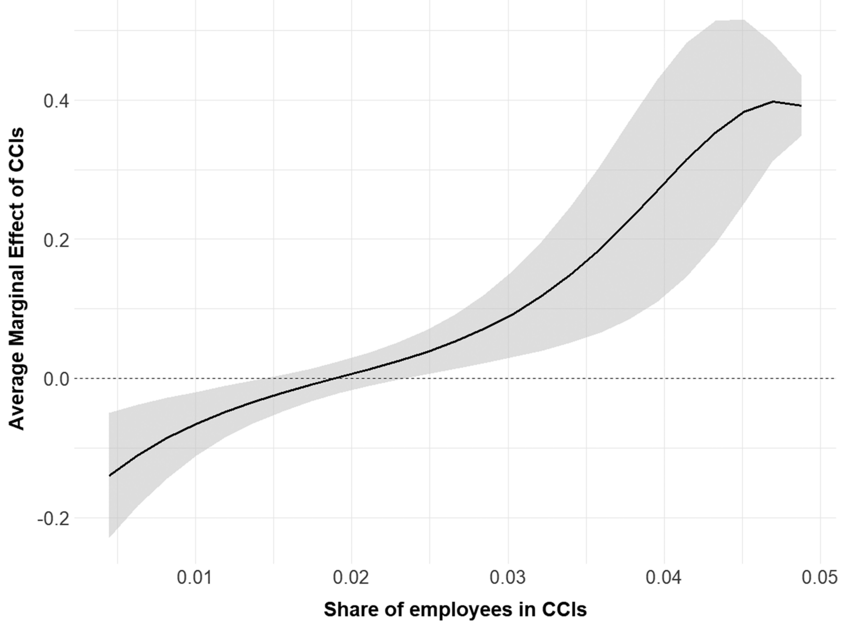

FIGURE 1 Average marginal effects of the share of employees in CCIs on the probability of creating a new CCIs-related sectoral specialization

CCIs is above the threshold of 1.9% and is significantly positive when it is above the threshold of 2.4%. Below the 1.9% threshold, the average marginal effect of the share of workers employed in cultural and creative industries on the probability of creating a new sectoral specialization is negative and close to zero.

These findings suggest that the presence of workers employed in CCIs does not necessarily help building up new specializations and boosting regional specialized diversification. In fact, it seems that CCIs need to achieve a certain level of critical mass in order to be able to generate positive spillovers allowing the local economy to increase its specialized diversification by building up new sectoral specializations. Unfortunately, the available data do not allow making any conclusion as to the mechanism behind these findings, nevertheless there might be some possible reasons explaining them. In particular, it seems that not only CCIs might be able to generate positive spillovers to the creation of new specializations in the related industries to CCIs (above a certain threshold), but their presence could be a "necessary" condition for these industries. It could be that a local presence of CCIs below a certain level does not justify or need the presence of related industries, which, in turn, might become profitable in the province only when CCIs reach a specific importance. Another possibility is that only the presence of CCIs in the local economy (with a certain degree of importance) might generate the spillovers and the knowledge needed to create new specializations in their related industries. It follows that if the local economy does not have enough presence of CCIs, it may lack the necessary spillovers, knowledge or need to create companies and employment operating in the industries related to CCIs.

These results are particularly relevant because they emerge from an estimation procedure also considering the change in the number of specialized sectors in each province. Hence, the estimates capture the relationship between the local share of employees in CCIs and the probability to build up a new specialization, net of any potential specialization substitution between sectors. Moreover, the results are also accounting for the relatedness between each sector and the structure of the local economy. As in Cortinovis et al. (2017), a high-density relatedness around sector *s* at year *t* is associated with a significantly higher probability that a province develops a new specialization in sector *s* five years later[13].

These results are robust across different dimensions. Indeed, Table 3 presents the estimates related to different specifications of model (3), in order to verify that these findings are consistent and not a spurious outcome of operationalization decisions.

In particular, the first two columns of Table 3 (model (4) and model (5)) consider as thresholds to determine specializations those combinations of sectors and provinces with a location quotient above 0.9 and 1.1, respectively. The results clearly indicate that the non-linear relationship between the share of employees in CCIs and the probability of building up a specialization in a CCIs-related sector which is new for the local economy is not specifically related to the way in which specialization is defined. Indeed, regardless of the location quotient threshold used to determine specialization, the results always indicate that the linear relationship of the local share of employees in CCIs is significantly negative, while the estimate for the quadratic interaction is significantly positive. Hence, these results confirm that the relationship between the share of employees in CCIs and the probability to increase the relative importance of CCIs-related sectors only becomes positive above a certain level of critical mass of CCIs.

The distribution of the variable EMPL_CCI ranges between 0.44% and 4.88%. However, there are three outliers in the upper part of the distribution (the province of Rome with 4.88%, the province of Milan with 4.19%, and the province of Florence with 3.35%) and one outlier in the lower part of the distribution (the province of Arezzo with 0.44%). All the other provinces are distributed in the interval between 1.5% and 2.9%. To verify that the results presented above do not depend on these outliers, the last two columns of Table 3 (model (6) and model (7)) present the estimation results when the outliers in the upper part of the distribution and the outlier in the lower part of the distribution are excluded, respectively. The results confirm the existence of a non-linear relationship between the

[13]Moreover, the findings highlight a negative relationship between total employment and the probability of building up a new sectoral specialization. This is in line with the literature on agglomeration economies (e.g., De Groot, Poot, & Smit, 2015), indicating that specialization dynamics are more common in relatively less urbanized areas. Indeed, to build up a new specialization in a more urbanized and populated area, a sector would need to grow more (in absolute terms) compared to a similar situation in a smaller area.

TABLE 3 Different specifications of the entry model on the development of new CCIs-related sectoral specialization in Italian provinces

	Model (4) Specialization if LQ > 0.9	Model (5) Specialization if LQ > 1.1	Model (6) without Rome, Milan, and Florence	Model (7) without Arezzo
EMPL_CCI	−0.9177*** (0.1540)	−0.5955** (0.2388)	−0.6956*** (0.1403)	−0.5706* (0.3341)
EMPL‾ CCI^2	1.0889*** (0.1868)	0.8968*** (0.3005)	0.9192*** (0.1655)	0.8981*** (0.3389)
RELATEDNESS	0.5031*** (0.0809)	0.8560*** (0.1108)	0.6457*** (0.1021)	0.6348*** (0.1025)
COMPLEXITY	0.1173 (0.1643)	0.0247 (0.1515)	0.0741 (0.1735)	0.0337 (0.1815)
EMPL_TOT	−0.4359** (0.1713)	−0.6895*** (0.2171)	−0.3774*** (0.1218)	−0.4879*** (0.1643)
GDP (*PER CAPITA*)	−0.2151 (0.1952)	−0.0262 (0.2098)	−0.2579 (0.1610)	−0.2867* (0.1694)
EDUCATION	0.1559 (0.1116)	0.1382 (0.1289)	0.0720 (0.1104)	0.0606 (0.1119)
R&D	0.0631 (0.0737)	−0.0124 (0.0752)	0.0341 (0.0644)	0.0366 (0.0642)
POP DENSITY	−0.0134 (0.0698)	0.0941 (0.0758)	0.0122 (0.0687)	0.0184 (0.0865)
ΔSPECIALIZATIONS	0.0254 (0.0611)	0.2715*** (0.0703)	0.2357*** (0.0647)	0.2349*** (0.0680)
CONSTANT	−4.3142*** (1.1517)	−3.2212*** (0.8520)	−3.3455*** (0.8463)	−3.3360*** (0.8469)
Region fixed effects	Yes	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes	Yes
Spatial Lag of X (SLX)	Yes	Yes	Yes	Yes
Log Likelihood	−1323.0	−1336.8	−1312.1	−1285.7
Observations	4,173	5,122	4,583	4,606

Notes: Clustered standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

local share of employees in CCIs and the provincial probability of building up a specialization in a CCIs-related sector. In both cases, the findings show that the linear relationship of the local share of employees in CCIs is significantly negative, while the estimate for the quadratic interaction is significantly positive. Moreover, given that the provinces of Rome and Milan are the two larger ones in Italy, model (6) also suggests that the previous findings are not driven by the bigger provinces.

Overall, these robustness checks highlight how the non-linear relationship between the share of employees in CCIs and the probability of building up a specialization in a CCIs-related sector is not linked to specific operationalization decisions or driven by the presence of outliers. Rather, these findings are robust and related to the fundamental linkages between CCIs and specialization processes.

5 | CONCLUSIONS

CCIs play an important role in the evolution processes characterizing our societies and are at the heart of the creative economy. Indeed, these sectors are at the forefront of innovation, generating spillovers stimulating other sectors through knowledge exchange and labour mobility between sectors, as well as the society at large as an intrinsic part of the entire system. With the rise of increasingly more complex and intertwined production processes and business models, CCIs are increasingly becoming a crucial element in the value chain of almost every product and service. However, given that the characteristics of CCIs can be territorially specific, these sectors are likely to provide heterogeneous contributions to local economic growth.

Even though the scientific debate on this issue is rich from a theoretical perspective, the related empirical evidences are still to be fully deployed (Cerisola, 2018). Moreover, while relatedness effects and CCIs have been found to be positively associated, it remains unclear whether and how the size and the characteristics of the latter matters for local economic development.

This study estimates an entry model analysing the ability of Italian provinces to successfully build up a specialization in a CCIs-related sector that is new for the province. The findings indicate that the relationship between the share of employees in CCIs and the probability of creating a new sectoral specialization is non-linear. In particular, the results show that CCIs need to reach a certain level of critical mass to be able to generate positive spillovers in the local economy. In that light, this paper proves that, above a certain threshold, the presence of workers employed in CCIs is positively related to regional specialized diversification and that the size of cultural and creative sectors matters.

These findings are consistent with previous empirical studies refuting a commonly accepted causal scheme by which cultural and creative workforce cause a multiplier effects by boosting the local economy in a sort of post-industrial Keynesianism (Crociata, et al., 2018; Cunningham, 2014; Markusen, 2006). The results of this paper support previous findings highlighting how regions with denser concentrations of CCIs are typically characterized by higher levels of economic prosperity (Power, 2011). Additionally, these results are in line with the analysis of Jeffcutt and Pratt (2009) and Chapain et al. (2010), indicating that concentrations of CCIs generate a stimulating environment encouraging the exchange of ideas (through, for example, processes of local labour mobility across sectors), reinforcing innovation processes and increasing the regional ability to turn new ideas into entrepreneurial opportunities. Finally, these findings are also consistent with the study of Lazzeretti et al. (2017), indicating that the lack of impacts of CCIs on the overall economy is probably due to a matter of dimension of the sectors analysed.

Policy-makers are increasingly acknowledging and supporting CCIs because their innovative power is essential for the further development of regional economies. The findings of this analysis highlight the need for CCIs-led policies to achieve a certain level of critical mass to allow local economies to benefit from positive spillovers and increase their diversification by building up new specializations. These results warn about the current hype on culture-led development policies, highlighting the need to acknowledge the heterogeneity of regional economic systems in order to successfully impact on local economic development. The mantra of the beneficial effects of culture and creativity should be targeted on the basis of the structural pattern of the local economies.

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APPENDIX A: DEFINITION OF THE CULTURAL AND CREATIVE SECTORS

TABLE A.1 Cultural and creative sectors according to the Guide to Eurostat Culture Statistics

C18.1.1	Printing of newspapers
C18.1.2	Other printing
C18.1.3	Pre-press and pre-media services
C18.1.4	Binding and related services
C18.2.0	Reproduction of recorded media
C32.2.0	Manufacture of musical instruments
G47.6.1	Retail sale of books in specialized stores
G47.6.2	Retail sale of newspapers and stationery in specialized stores
G47.6.3	Retail sale of music and video recordings in specialized stores
J58.1.1	Book publishing
J58.1.3	Publishing of newspapers
J58.1.4	Publishing of journals and periodicals
J58.2.1	Publishing of computer games
J59.1.1	Motion picture, video and television program production activities
J59.1.2	Motion picture, video and television program post-production activities
J59.1.3	Motion picture, video and television program distribution activities
J59.1.4	Motion picture projection activities
J59.2.0	Sound recording and music publishing activities
J60.1.0	Radio broadcasting
J60.2.0	Television programming and broadcasting activities
J63.9.1	News agency activities
M71.1.1	Architectural activities
M74.1.0	Specialized design activities
M74.2.0	Photographic activities
M74.3.0	Translation and interpretation activities
N77.2.2	Renting of video tapes and disks
P85.5.2	Cultural education
R90.0.1	Performing arts

(Continues)

TABLE A.1 (Continued)

R90.0.2	Support activities to performing arts
R90.0.3	Artistic creation
R90.0.4	Operation of arts facilities
R91.0.1	Library and archives activities
R91.0.2	Museums activities
R91.0.3	Operation of historical sites and buildings and similar visitor attractions

APPENDIX B: RELATEDNESS MEASURE

Following the product space arguments of Hausmann and Klinger (2006), Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), we adapt the measure of density relatedness to our empirical analysis. The density relatedness—henceforth relatedness—measures the average proximity[14] of sector s to the local current productive structure of province p (Boschma et al., 2012; Cortinovis et al., 2017), as shown in the following Equation:

$$Rel_{s,p} = \frac{\sum_j \phi_{s,j} X_{j,p}}{\sum_j \phi_{s,j}}, \tag{A1}$$

where,

$$X_{j,p} = \begin{cases} 1 & if\ LQ_{j,p} \geq 1 \\ 0 & otherwise \end{cases}$$

where j refers to sector j and LQ is for location quotient, as defined in Section 3. $\phi_{s,j}$ refers to the proximity between sectors j and s. $X_{j,p}$ is a dummy variable taking value 1 if province p is specialized in sector j. Hence, $Rel_{s,p}$ measures the relatedness around sector s in province p, and is computed as the sum of proximities between sector s to all the sectors that province p is specialized in, divided by the sum of proximities between sector s to all industries. The relatedness indicator ranges from zero to one: high relatedness values indicate that the pth province has many potential sectors surrounding the sth sector; a value of zero means that province p has no specialization in any sector related to sector s; when province p is specialized in all the industries which are related to sector s, $Rel_{s,p}$ is equal to one.

APPENDIX C: ECONOMIC COMPLEXITY MEASURE

Following Hidalgo and Hausmann (2009), we compute the economic complexity index (ECI) for the NUTS3 Italian regions (provinces) over the period 2012–16. This approach is based on the idea that the availability of capabilities in

[14]The proximity index between sector s and j is computed by taking the minimum between the conditional probability of a region being specialized in sector s given it is specialized in sector j, and the conditional probability of a region being specialized in sector j given it is specialized in sector s, as follows:

$$\phi_{s,j} = min\left(P\left(x_s | x_j\right), P\left(x_j | x_s\right)\right), \tag{A2}$$

where for any region or country p:

$$x_{s,p} = \begin{cases} 1 & if\ LQ_{s,p} \geq 1 \\ 0 & otherwise \end{cases}, \tag{A3}$$

where LQ is the location quotient, as defined in Section 3, and the conditional probability is calculated using all Italian provinces. Since conditional probabilities are not symmetric this measure takes the minimum of the probability of being specialized in sector s given j and the reverse, to make the measure symmetric and more stringent.

a province can be inferred from export data. Here, ECI is computed following the same approach, using employment data[15] instead of trade data. Since we expect provinces with more capabilities to have a wider variety of occupations, that is, to be more diversified, than provinces with fewer capabilities, diversification is a proxy for the number of capabilities present in a province. However, diversification in itself is not the most accurate estimator of the number of capabilities available in a province, since provinces having the same number of occupations could require a different number of capabilities (because it could have more complex occupations).

The diversification index needs to be corrected by the number of capabilities required by an occupation. This can be done by looking at the ubiquity of the occupations present in a province. Occupations that require many capabilities will be more likely diffused in few provinces, and vice versa. The ubiquity of occupations, therefore, carries information about their complexity, which can be used to correct diversification as an effective measure of the number of capabilities available in a province

The LQ, as defined in Section 3, is computed to measure the level of specialization of sector s in province p relative to the overall specialization of sector s in all provinces in our sample. The computation of the location quotient represents the first step to build the bipartite network in which provinces are connected to the sectors in which they are specialized in. Formally, the bipartite network is represented through the adjacency matrix $M_{s,p}$, where $M_{s,p}$ = 1 whenever the location quotient is larger than a certain threshold. More specifically, this study considers $M_{s,p}$ = 1 whenever province p is specialized in sector s, (i.e., whenever the location quotient is larger than one) and zero otherwise. Mathematically, the adjacency matrix is built as follows:

$$M_{s,p} = \begin{cases} 1 & if\ LQ_{s,p} \geq 1 \\ 0 & otherwise \end{cases}. \tag{A4}$$

From the adjacency matrix it is then possible to compute $k_{p,0}$, representing the degree of *diversification* of province p, which is the sum of the number of sectors in which the province is specialized in:

$$k_{p,0} = \sum_s M_{s,p}. \tag{A5}$$

Additionally, Hidalgo and Hausmann (2009) define the *ubiquity* of sector s in the bipartite network as:

$$k_{s,0} = \sum_p M_{s,p}, \tag{A6}$$

which is the sum of the number of provinces specialized in product s. Diversity and ubiquity are used to make sequential corrections for one another. Consequently, the measures of knowledge complexity for both provinces and sectors can be computed by sequentially combining the measures of diversity and ubiquity in the following two equations over a series of n iterations:

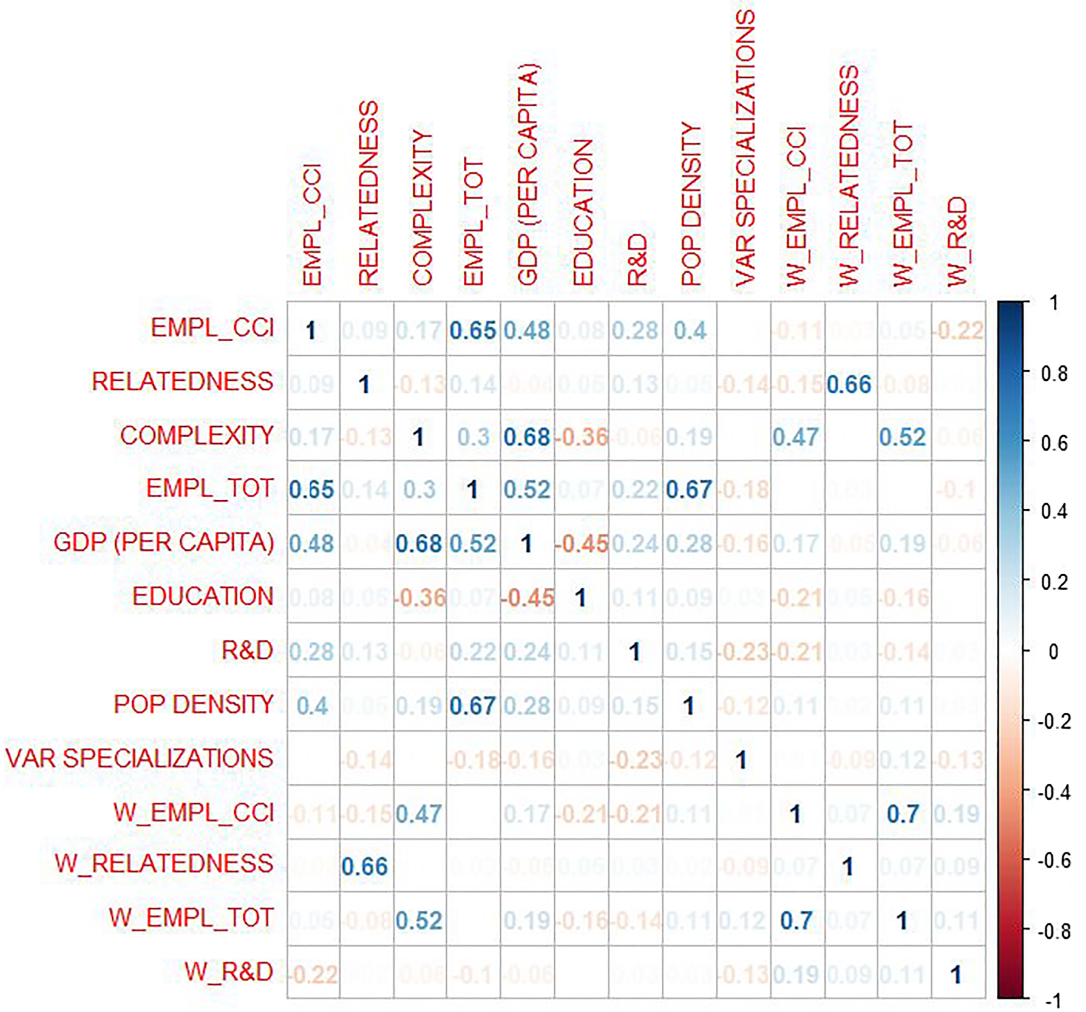
$$k_{s,n} = \frac{1}{k_{s,0}} \sum_p \left(M_{s,p} \cdot k_{p,n-1} \right), \tag{A7}$$

$$k_{p,n} = \frac{1}{k_{p,0}} \sum_s \left(M_{s,p} \cdot k_{s,n-1} \right). \tag{A8}$$

[15]The use of employment data allows constructing an industry space connecting all sectors of the economy, including non-tradable sectors. As the economic structure of a region can be approximated by its occupational composition, the size of sectors (in terms of number of employees) can be understood as the expression of the knowledge and knowhow that are embodied in it. The production space drawn in this study connects industries employing similar workers, namely, workers embedding similar skills and capabilities.

This iterative procedure, referred to as "the method of reflections", allows extracting relevant information about the availability of capabilities in Italian provinces and sectors. Indeed, each additional iteration (or reflections) in $k_{p,n}$ provides increasingly more precise measures of the ECI as the noise and size effects are eliminated. In fact, the ECI is represented by $k_{p,n}$ with n going to infinity. However, for practical reasons, the iterations are stopped when the rankings of provinces and sectors are stable from one step to another (i.e., no further information can be extracted from the structure of the province-sector network). More specifically, the iteration process is stopped at n = 12, as all of the ECI provincial values converge to the same level. Subsequently, the analysis follows Hidalgo and Hausmann (2009) and considers information from the tiny deviations of these converging values.

APPENDIX D: CORRELATION BETWEEN THE EXPLANATORY VARIABLES



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Resumen. Este artículo tiene por objeto analizar la forma en que la presencia de trabajadores empleados en las industrias culturales y creativas (ICC) está relacionada con la diversificación regional especializada. Desde una perspectiva teórica, las ICC impulsan el desarrollo económico y la capacidad de innovación local debido a su papel de facilitación de procesos de fecundación cruzada de ideas. Este estudio estima un modelo básico que analiza la capacidad de las provincias italianas para crear con éxito nuevas especializaciones sectoriales. Los resultados indican que la relación entre la proporción de empleados en las ICC y la probabilidad de crear nuevas especializaciones sectoriales no es lineal, lo que pone de relieve la necesidad de que las políticas dirigidas a las ICC alcancen un cierto nivel de masa crítica para tener éxito.

抄録: 本稿では、文化創造産業で働く労働者の存在が、どのように地域に特化した多様化と関連しているかを分析する。理論的な観点からは、文化創造産業は、異業種間でのアイデアの交換を促進することにより、経済発展と地域のイノベーション能力を刺激する。本研究では、新たな産業別特化(sectoral specialization)の創造を成功に導くイタリアの県の能力を分析する入力モデルを推定する。結果から、文化創造産業で働く労働者の割合と新たな産業別特化が創造される可能性との関連性は非線形であることが示され、成功するためには、文化創造産業主導の政策が一定の量に達する必要があることが強調される。