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Creativity and the City: Testing the Attenuation of Agglomeration Economies for the Creative Industries in Barcelona

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Document de treball n.10- 2017

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Edita:

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www.fcee.urv.es/departaments/economia/public_html/index.html
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Adreçar comentaris al Departament d'Economia / CREIP

ISSN edició en paper: 1576 - 3382
ISSN edició electrònica: 1988 - 0820

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Creativity and the City: Testing the Attenuation of Agglomeration Economies for the Creative Industries in Barcelona

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Abstract:

The aim of this paper is to infer the spatial extent of agglomeration economies for the creative service industries (SCI) in Barcelona and its relationship with firms' performance. Using data from Mercantile Register (SABI) that provides micro-geographic data of firms between 2006 and 2015 I estimate the effect of intra-industry and inter-industry agglomeration in rings around location on productivity in Barcelona. Main results are that, (1) for CSI, at a micro-spatial level, localisation economies are not so relevant, although much work still remains to be done on this issue; (2) while for Non-SCI having creative workers in the near proximity (250 metres) seems to enhance their productivity; and (3) for the symbolic-based CSI localisation economies – mainly understood as networking and knowledge externalities – have positive effects on TFP at shorter distances (less than 250 metres), while for the two other knowledge-based CSI (i.e., synthetic and analytical) localisation economies seem not to be so relevant. These results strongly suggest the importance of networking or information spillovers in CIs, which are strongly concentrated in the largest cities.

Keywords: creative industries, agglomeration economies, distance-based methods, micro-geographic data, Barcelona

*This paper was partially funded by ECO2013-42310-R, ECO2014-55553-P, the "Xarxa de Referència d'R+D+I en Economia i Polítiques Públiques", the SGR programme (2014-SGR-299) of the Catalan Government, the "Departament d'Universitats, Recerca i Societat de la Informació de la Generalitat de Catalunya" and the "Fundación SGAE". We would like to acknowledge research assistance by M. Lleixà and the helpful and supportive comments of JM Arauzo, M. Manjón, A. Moreno and C. Turcu and the participants at the 5th WIPE, the 19th Annual Conference of the Network for Economic Research (INFER) and the 2017 Edition of the Summer School in Urban Economics. Any errors are, of course, our own.

1. INTRODUCTION

Creative Industries (CIs) are defined as knowledge-based activities based on individual creativity, skill and talent, having the potential for wealth and job creation through the development of intellectual property; they include activities like Arts, Advertising, Cinema, Fashion Design, Publishing, R&D or Software (DCMS 2001; UNCTAD 2010). In an increasingly global world, CIs emerge as a new driver for local economic growth, regional differentiation and urban regeneration through their role in the innovation and economic evolution process (Stoneman 2010; Potts 2015). All these factors have increased the interest on their study over the last years.

As CIs are characterised by a high proportion of small firms and a project-based nature requiring constant explicit and tacit contact within formal and informal networks, advantages exist for employed in creative sectors in agglomerating in the same areas (Caves 2000; Pareja-Eastaway 2016). In this sense, geographical proximity can certainly facilitate the exchange of knowledge between different agents working in the same area; particularly, if knowledge is tacit and context-specific, it requires repeated contact with others (see for instance, Scott 1997; Banks et al. 2000; Tschang and Vang 2008 or Lazzeretti et al. 2008, 2012). Because of all that, CIs have an essential need for agglomeration in comparison to non-creative activities (Scott 1997 p. 329; Feldman 2000, p.378-379; Andersson et al. 2014, p.130). The main concept behind agglomeration literature is the idea that spatial concentration – either population or human capital – enhances productivity. Nevertheless, previous contributions in the literature about CIs agglomeration use aggregated data and area-based measures, leading to the well-known Modifiable Area Unit Problem (MAUP)[1]. Therefore, this approach leaves some fundamental questions unanswered: What is the spatial extent of externalities associated with the agglomeration of CIs? How quickly do these external economies attenuate with distance? These questions are even more relevant when agglomeration effects are proved not to spill much over space (Rosenthal and Strange 2008; Arzaghi and Henderson 2008). These questions are important both for firms' location decisions and for local economic development policies focusing on urban regeneration, attraction of skilled workers and generation of creative and innovative environments. Nevertheless, the

[1] The MAUP appears when the same analysis is applied to the same data, but different aggregation schemes are used, involving biased results. See Arbia (2001) for more details.

effect of the spatial extent of the agglomeration economies on creative business productivity within urban areas has not been yet analysed in the existing literature (e.g., Cooke and Lazzeretti 2008; De Propris et al. 2009; Lazzeretti et al. 2012; Boix-Domenech et al. 2015).

In this paper we focus on the city of Barcelona. Barcelona accounts for more than 7,000 creative firms (the 7.5% of total firms in the city) and more than 100,000 employed in CIs (the 49% of the employment in CIs in Catalonia) (Ajuntament de Barcelona and IERMB, 2013). Since some years ago, Barcelona is engaged in a process of transformation into an economy oriented to innovation, creativity and culture. In this sense, this cultural and creative reputation has transformed Barcelona into a great magnet for creative activities and high-skilled workers. However, this increasing attraction may turn into disagglomeration economies in terms of higher rentals prices, congestion and gentrification problems. Nevertheless, according to the existent literature on the CIs agglomeration, CIs essentially need for spatial proximity and to locate around city centres in order to benefit from networking possibilities, face-to-face interaction and urban amenities such as cultural infrastructures, diversity of people and activities, or place-specific image (Arzhagi and Hendersson 2008; Currid and Williams 2010; Boix-Domenech et al. 2015). Still, and as Coll-Martínez et al. (2016) pointed out, previous studies have not yet considered how demand factors could mitigate this agglomeration advantages for CIs and how they could explain the fact that this CIs tendency to coagglomerate remains consistent wherever they locate (Currid and Williams 2010).

The aim of this paper is to infer the spatial extent of agglomeration economies for the CIs in Barcelona and its relationship with creative firms' performance. Concretely, I try to control for demand factors in order to identify the actual role of the specific characteristics (i.e., networking opportunities, cultural amenities) traditionally explaining the agglomeration of CIs on the urban centre. I use data from Mercantile Register (SABI) that provides micro-geographic data of firms between 2006 and 2015. I estimate the effects of intra-industry (among CIs) and inter-industry (non-CIs) agglomeration in rings around location on productivity in Barcelona. With this fine level of geographic detail, agglomeration measures are computed by using Geographical Information Systems (GIS). For each creative firm and year, I compute a density measure counting the number of neighbour firms located within each distance band defined around the reference firm. By using this strategy I can avoid the MAUP issue and provide a more detailed analysis on the attenuation of agglomeration economies.

The fundamental findings in the paper are that, (1) for CSI, at a micro-spatial level, localisation economies are not so relevant, although much work still remains to be done on this issue; (2) while for Non-SCI having creative workers in the near proximity (250 metres) seems to enhance their productivity; and (3) for the symbolic-based CSI localisation economies – mainly understood as networking and knowledge externalities – have positive effects on TFP at shorter distances (less than 250 metres), while for the two other knowledge-based CSI (i.e., synthetic and analytical) localisation economies seem not to be so relevant. These results strongly suggest the importance of networking or information spillovers in CIs, which are strongly concentrated in the largest cities.

We have structured the paper as follows. In next section we review the literature on the relationship between agglomeration economies and firm productivity and also the main factors explaining the agglomeration and coagglomeration of CIs. In Section 3 we present the empirical approach. In Section 4 we present the data and in Section 5, main results. Finally, in Section 6 we discuss main conclusions.

2. RELATED LITERATURE

2.1. Agglomeration and firm productivity

The literature on agglomeration economies – defined as those benefits in terms of productivity derived from the spatial concentration of jobs and firms – identifies the local externalities arising from the concentration of economic activities in space. According to Hoover (1936), agglomeration economies are subdivided into intra-industry (localisation) and inter-industry (urbanisation) economies. Localisation economies arise from the spatial concentration of firms operating in the same industry (Marshall 1920). In this sense, firms located close to other firms operating in the same industry benefit from reduced transportation costs, emergence of external-scale economies, availability of specialised workers and suppliers, and diffusion knowledge and technological spillovers which reduce economic costs, enhancing efficiency and growth (Glaeser et al., 1992; Duranton and Puga, 2004; Martin et al., 2015). Regarding urbanisation economies, they arise from the spatial concentration of different economic activities and from the diversity of urban environment characteristics. Thus, firms benefit from the availability of inputs from suppliers operating at different stages in the production chain, and cross-fertilisation among existing ideas and technologies favoured by the variety in the local economic structure (Jacobs 1961, 1969).

Empirical analysis of the role played by agglomeration economies on total factor productivity (TFP) has become especially relevant in the last decade (Ciccone and Hall 1996; Henderson 2003; Martin et al. 2015). Other approaches evaluate the impact of these agglomeration forces on employment growth (Glaeser et al. 1992; Henderson et al. 1995). However, their findings are difficult to generalise due to the diversity of results. For instance, Henderson (2003) found strong positive effects of localisation economies on productivity at plant level on US high-tech industries, but not in machinery industries, and he finds little evidence of diversification economies. The same study finds a negative effect of localisation and a positive effect of diversification externalities on employment growth, thus confirming the results of Glaeser et al. (1992). Finally, Martin et al. (2015) found that French firms productivity benefits from localisation, but not from diversification economies. However, benefits from industrial clustering are quite modest in magnitude.

The spatial scale of agglomeration economies is a relevant issue in this literature (Scott 1982; Rosenthal and Strange 2003; Combes and Gobillon 2014). Previous contributions capture agglomeration economies according to predefined geographic limits, such as SMAs, LLs and NUTS-2 or NUTS-3 administrative units. Then, economic activity is spatially divided according to these administrative boundaries. However, due to agglomeration effects on productivity can differ across geographical scales and they also are likely to attenuate with distance, the changing of the shape and size of spatial units is usually necessary. Therefore, this traditional spatial analysis can bring to the MAUP. The

MAUP leads to empirical results biased across geographical scales (Arbia, 1989).[2] In this sense, the MAUP could partially explain the divergence of results in empirical works analysing the relationship between agglomeration economies and firms productivity. These differences can be explained by the use of different geographic units and the approaches to measure agglomeration (Rosenthal and Strange 2003).

Moreover, as it is highlighted above, agglomeration effects are likely to attenuate rapidly over space (Rosenthal and Strange 2003, 2008; Arzaghi and Henderson 2008). Indeed, this fact may change between localisation and urbanisation externalities, as well as by different types of agglomeration forces (Martin 1999). For instance, knowledge spillovers are thought to occur at shorter distances (i.e., within cities or neighbourhoods) than input-output linkages (i.e., counties, regions), since the former require face-to-face interaction to be developed. In this context, there are few papers that have tried to measure the scale and spatial extent of agglomeration economies. One of the approaches to deal with that issue is to compute a density-based measure counting the number of neighbour firms located within rings defined around the reference firm with increasing radius. Distance-based methods are seen as an alternative to deal with the measurement of agglomeration of economic activities (Duranton and Overman 2005; Marcon and Puech 2010). Their main advantage is that when considering space as continuous, they avoid the use of predefined spatial units and their related problems (i.e., the MAUP). In the existent literature there only few papers considering this approach and most of them focus on USA data. Rosenthal and Strange (2003, 2005, and 2008) analyse the attenuation of agglomeration effects on new firm creation and individual wages and find that they attenuate after five miles. Desmet and Fafchamps (2005) do the same for employment growth and found positive externalities effects for service jobs up to 20 km and for non-service jobs they appear between 20 to 70km. Arzaghi and Henderson (2008), for advertising agency industry, found that there is an extremely fast spatial decay of agglomeration effects occurring primarily within 500 metres. Finally, for the Italian case, Di Addario

[2] The MAUP appears when the same analysis is applied to the same data, but different spatial aggregation schemes are used, involving different results. MAUP takes two forms: the scale effect and the zone effect. The scale effect exhibits different results when the same analysis is applied to the same data, but changes the scale of the aggregation units. The zone effect is observed when the scale of analysis is fixed, but the shape of the aggregation units is changed. See Arbia (2001) for more details.

and Patacchini (2008) found that the impact of local population size is strongest between 0 and 4 km and is no significant any more beyond 12 km. In all them, the spatial scope of agglomeration effects is given by the distance after which the local characteristic does not have a significant effect any more. It is possible to find that agglomeration effect first increase with distance before decreasing. Then, this turning point gives the spatial scale at which they are the strongest (Combes and Gobillon 2014).

2.2. Creative Industries, agglomeration and productivity

The aforementioned CIs characteristics – their propensity for project work and networking, the unpredictability of demand, and the need for continuous novelty and innovation closely associated to aesthetics and symbolic values (Caves 2000) – and their potential for economic growth as a source of creativity and innovation have increased the interest on studying their location behaviour. In this sense, previous studies analysing the location patterns of CIs underline their tendency to be highly concentrated in space (Cooke and Lazzeretti 2008; Lazzeretti et al. 2008, 2012).

Traditional factors explaining the concentration of economic activities in space can also be applied to agglomeration of CIs. In this sense, CIs may benefit from localisation and urbanisation economies. Regarding the former, CIs may agglomerate with firms of the same industry to take advantage of local knowledge spillovers, to benefit from pooled specialised labour markets and the availability of local suppliers specialised in other parts of the creative filière (Landry 2000; Florida 2002; Maskell and Lorenzen 2004; Scott 2006; Santagata and Bertacchini 2015; Lazzereti et al 2012; Branzanti 2014).

Regarding urbanisation economies, CIs coagglomerate to take advantage from the diversity of economic activities and people, and from the capacity of local consumption markets (Lorenzen and Frederiksen 2008; Lazzeretti et al. 2012). This diversity found in urban areas can facilitate the coordination among diverse knowledge bases, and their geographical proximity promotes knowledge flows, the spread of ideas, and new forms of entrepreneurship among different agents and industries (Glaeser et al. 1992; Flew 2014). At the same time, demand-side factors should be considered as well. In fact, the coagglomeration of CIs could be explained simply by the same reasons inducing the location of service activities in urban areas. That is, these areas are a focal point where firms have access to a greater range of consumer's preferences having high average levels of cosumption of culturals goods and services (Heilbrun 1996; Glaeser 2001; Turok 2003; Currid and Williams 2010). In short, creative activities actually benefit from their colocation for the same reasons as other industries do – that is, coagglomeration brings the possibility to benefit from static and dynamic increasing returns effects (i.e., flexible subcontracting opportunities, learning and innovation phenomena, entrepreneurial spinoff possibilities, etc.); but they may require more concentration for their economic and social interactions (Scott 2000; Banks et al. 2000; Currid and Williams 2010).

One of the main drivers for agglomeration and coagglomeration of CIs at intra-metropolitan level is their type of dominant knowledge base. In the literature we can find three different definitions of knowledge bases for innovative and creative activities: analytical, synthetic and symbolic. All of them are defined according the mixture of tacit and codified knowledge, the possibilities and limitations of knowledge codification and the competences and skills required for the development of their activity (Asheim and Parrilli 2009, 2012). Analytical knowledge base refers to activities where knowledge is highly codified and the need of tacit interaction is lower (as in R&D and Engineering activities). Synthetic knowledge base is partially codified, requires more tacit knowledge, and it is more dependent on the context (as in Architecture and Software and computer-related activities). Finally, symbolic knowledge base is associated to the creation of new ideas and images and it is highly tacit and context-specific (as in Advertising, Arts, Cinema, Fashion design, Publishing, and TV and Radio).

Thus, as most CIs rely on tacit (face-to-face) interaction between creative agents and on the specific environment of the area where they operate, they are expected to agglomerate in a more intensive way than non-creative manufacturing activities (Scott 1997, Feldman 2000). For the same reason, their concentration can also be highly sensitive to distance-decay (Arzaghi and Henderson 2008; Boix-Domenech et al. 2015). Thus, we could expect to find a positive effect and rapid distance decay for the agglomeration of CIs than for other industries with a similar firm-size distribution, and these results may change according to the dominant knowledge base of each creative sector.

Some authors argue that these factors provide only a partial explanation on the determinants of location of CIs (Tschang and Vang 2008). In this sense, CIs may agglomerate because of the existence of historical and cultural infrastructures which are essential sources of inspiration for employed in CIs; infrastructure of specialised public and social actors providing support to these activities (e.g., education and training institutions, government funded agencies, gatekeepers and private lobbying organisations); 'soft characteristics'[3] or amenities in terms of quality of life, tolerance, cosmopolitan environments; a particular identity o place image[4] also facilitates the attraction of creative talents and entrepreneurs (Scott 2000; Andersson and Andersson 2008; Pareja et al. 2008; Murphy et al. 2014; Coll-Martínez and Arauzo-Carod 2015).

However, intra-metropolitan analysis of the agglomeration of CIs should consider that, in fact, there is a heterogeneous distribution of amenities and cultural infrastructures across neighbourhoods within the city (Currid and Williams 2009, p. 425). In this sense, if CIs are mainly attracted to those well-located neighbourhoods where 'things happen' (i.e. social and networking events), we could expect to find creative activities highly coagglomerated in some locations of the city, and a rapid decay of this agglomeration once we move away from these focal points. At the same time, the increasing attraction of these trending neighbourhoods could involve the dispersion of creative activities. That is, once these neighbourhoods increase their popularity due to all the advantages their offer, the rise of rental prices as well as those of other services is expected for these areas (as Pallares-Barbera et al. 2012 and Paül-i-Agustí 2014 find for Barcelona's neighbourhoods). As a result, some CIs activities may decide to locate in other areas where life and activity costs are more affordable (Chapain and Communian 2010). Moreover, the possibility of teleworking nowadays, more feasible than ever before due to the advances in information technology systems, can enhance the dispersion of creative workers (Moriset 2003).

[3] We refer to soft characteristics as the 'specific urban amenities' that create an environment that attracts people who are key to the most promising economic activities for the economic development of the urban region' (Musterd and Bontje 2010 p. 25). The use of the term 'soft' is related to these factors are difficult to measure or define (Clark et al. 2002; Pareja et al. 2008; Murphy et al. 2014).

[4] We refer to place image as those intangible and symbolic values defining the identity, uniqueness and social habits and norms of a place. And this place-specific image is more relevant for CIs working with high levels of aesthetic or semiotic content and where informal know-how and tacit forms of knowledge play a major role (Scott 2006). In fact, soft characteristics and place-image are closely related, since both are linked to a 'system of associative structures and social networks, connections and human interactions that underpins and encourages the flow of ideas between individuals and institutions' (Landry 2000, p133).

All in all, creative firms willing to benefit from all aforementioned factors will accept to suffer from classical inconvenients of core areas (e.g., higher rental prices) as those competitive advantages arising from agglomeration advantages (e.g., information flows through face-to-face interaction, networking possibilities and specific environments) were large enough to compensate them. Thus, I expect to find spatial decay within the first kilometre.

3. EMPIRICAL STRATEGY

3.1. The model

As it has been introduced in Section 2, agglomeration economies are generally assumed to improve TFP of firms through localization economies and urbanization economies. As I have access to firm-level data, this allows me to use an empirical strategy based on the estimation of a Cobb–Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\propto} L_{it}^{\beta} \tag{1}$$

where Y_{it} is value-added of plant *i* at time *t*, A_{it} is TFP, $K_{it}^{\propto}$ the capital stock and $L_{it}^{\beta}$the labour force (in terms of employees) of firm *i* at time *t*. I then assume that TFP of firm *i* depends on a firm-level component, U_{it}, but also on its immediate environment in terms of localization and urbanization economies, and a set of controls:

$$A_{it} = \left(LOC_{it}^{D}\right)^{\delta} (URB_{it})^{\gamma} X_{it}^{\sigma} U_{it}\ , \tag{2}$$

where LOC_{it}^{D} capture the local agglomeration externalities (CSIs) computed within different distance bands *D* for firm *i* and at time *t* ; URB_{it} capture urban agglomeration externalities (non-CSIs); and X_{it}^{σ} is a set of neighbourhood-firm variables for firm *i* and time *t*. Log-linearizing expressions (1) and (2), one obtains:

$$y_{it} = \propto k_{it} + \beta l_{it} + a_{it}, \tag{3}$$

and

$$a_{it} = \sum_{d=1}^{D} \delta\, loc_{it}^{d} + \sum_{f=1}^{F} \beta_f urb_{it}^{F} + \sum_{k=1}^{k} \beta_k X_{it}^{k} + u_{it} \tag{4}$$

where lower-case letters denote the log of upper-case variables in Eqs. (1) and (2). Following Martin et al. (2015), my strategy consists first in estimating Eq. (3) for CIs in order to obtain a_{it}. I then estimate

Eq. (4). Here, Eq. (3) can be used to relate TFP to some local characteristics, which can determine the channels through which agglomeration economies operate.

3.2. Estimation issues

Consistent estimation of the parameters of a production function is a problematic issue to cope with. Concretely, as output, labour, and other inputs are simultaneously determined by the firm, then inputs are likely to be endogenous variables because the error term of the model typically contains unobservable output determinants, involving potentially inconsistent estimates of the coefficient from ordinary least squares. To deal with these issues several approaches have been developed during the last decades (Van Beveren 2010). Among them, sophisticated semi-parametric approaches to control for unobservables making use of additional information on investment (Olley and Pakes 1996) or intermediate consumption (Levinson and Petrin 2003) stand out. However, according to Ackerberg, Caves and Frazer (2015) these estimation strategies may suffer from identification issues. For this reason they propose an estimation procedure relying on Olley and Pakes (1996) and Levinson and Petrin (2003) two-stage procedures but that estimates all the input coefficients in the second stage.[5] Because of that I follow Ackerberg, Caves and Frazer (2015) approach by using Manjón and Mañez (2016) procedure to estimate TFP in Stata (*acfest*). This approach is estimated by (nonlinear, robust) generalized method of moments. After estimation, it is possible to predict the estimated productivity of the firms in the sample. Doing so, I obtain standard estimates for inputs elasticities, around 0.8 for labour and around 0.40 for capital.

When estimating agglomeration economies and production functions endogeneity issues arise. Endogeneity at the local level can arise because some missing variables can simultaneously determine agglomeration economies and the local outcome. Here reverse causality is a relevant issue when higher outcome levels attract more firms and workers, and that increases the quantity of local labour and thus

[5] Since some authors strongly recommend comparing different approaches before choosing among them (Combes and Gobillon 2014), I have also estimated TFP by following Levinson and Petrin (2003) approach and by OLS. Still, as results do not seem to vary significantly I only present TFP results according to Ackerberg, Caves and Frazer (2015) approach.

density, at the same time. If this it is the case, a positive bias in the estimated coefficient of density is expected.

In order to deal with the aforementioned issues, Combes and Gobillon (2014) summarise main approaches to deal with these issues. In this sense, the use local fixed effects, instrumental variables, the generalised method of moments (GMM) and natural experiments are the main approaches used in this literature. The first approach to deal with such issues is the use of local fixed effects. However, this approach may have some disadvantages also. Concretely, it does not deal with missing variables that evolve over time; time invariant local fixed effects do not help in solving the endogeneity issue when is due to reverse causality; and identification relies on the time variations of the local outcome and local determinants of agglomeration economies only. An alternative approach can consist on finding the accurate instruments that can cope with both reverse causality and missing amenities. Instruments should verify two conditions: relevance and exogeneity. Previous works usually work with historical values of population or density or geographical characteristics. A third strategy could to cope with the aforementioned endogeneity issues when having panel data is to use a GMM approach to estimate the specification in first difference while using lagged values of variables as instruments. Even the same authors do not recommend relying on this approach when the final aim is to identify the role of local determinants on local outcomes. Therefore, choosing one or another is a complex decision and requires a careful methodological design.

For this reason, in this preliminary version of the paper I try to estimate TFP on some factors influencing firms' performance by using different approaches. Still, working with panel data offers some advantages over cross-section data as highlighted in Hsiao (2014). The introduction of standard fixed effects on the regression will potentially reduce the correlation effects of the explanatory variables with unobservables, as well as the use of one-year time lags. I also rely on fixed effects estimation procedure with and without using instrumental variables.

3.2.1. Identification and instruments

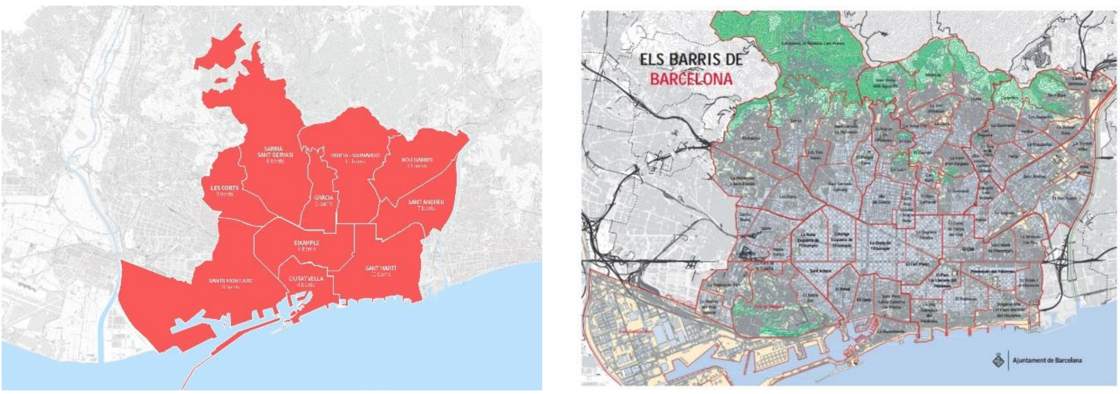
By focusing on Barcelona, unobserved neighbourhood characteristics include trendy places, construction, security, and neighbourhood public services for firms that can change over time. Thus, I choose particular historical variables from the 1990 Census as instruments for population density. This strategy should mitigate the omitted variables bias. Here, I justify the relevance of these instruments (see Ciccone and Hall 1996; Combes et al. 2008). The number of housing units in 1990 and the historical urban population in 1900 are usually found to be extremely relevant instruments, indicating major inertia in the distribution of population over space. If lags are long enough, they are thought to be exogenous because of changes in the type of economic activity (i.e., agriculture to manufacturing then services). I also control for distance to *Plaça Catalunya* as the commercial centre of the city.[6]

4. DATA AND VARIABLES

The firms in this dataset are located in Barcelona city. It is located in Catalonia, an autonomous region in north-eastern Spain. Barcelona has an area of 101.9 km2 and hosts more than 1.6 million people. In economic terms, it accounts for 31% and 6% of the Catalan and Spanish GDP, respectively. Barcelona is composed of 10 districts and 75 neighbourhoods (see Figure 1).

Figure 1. *Study of Area: Barcelona*

Districts *Neighbourhoods*



Source: http://w20.bcn.cat and http://www.bcn.cat/publicacions/Cartografia/

This study uses micro-geographic data from the SABI database (Bureau van Dijk). SABI contains omprehensive information on firms in Spain, detailed by firms' geographical information (plain coordinates), employment, and among others characteristics at the 4-digit NACE level. The SABI's

[6] In future version I will use also past values of current employment rings as the stocks of current workers on CSI are also potentially endogenous variables. Especially if there is a persistence effect on the location of current employment stocks.

data covers all limited liability firms and corporations, and does not include data from either self-employment neither or public employment.[7]

This paper follows UNCTAD's (2010) classification of CIs, the most widely accepted classification. UNCTAD's classification is the broadest available in terms of industries, including both manufacturing and service industries. Even so, the relevance of service creative firms is greater than manufacturing ones. Here I consider only Creative Service Industries (CSI) as Boix-Domenech and Soler-Marco (2015a) suggested further research should focus exclusively on CSI because in most regions examined activities classified as belonging to creative manufacturing were not in fact engaged in creating but in making. Concretely, among these CSI the analysis will focus on symbolic-based CSI (see NACE Rev. 2 industry classification in Table 1), which are found to agglomerate more intensively in the centre of Barcelona than the rest of CIs (Coll-Martínez et al. 2016). Moreover, in Table A1 (Annex) the temporal composition of the number of incumbents of CSI firms depicts growth on the first period followed by a period of attrition for both CSI and Non-CSI, following the economic trend of the period.

[7] In the literature we can find several studies using this database (Duch et al. 2009, Jofre and Solé-Ollé 2009 or Jofre et al. 2015) and some of them have explored its representativeness by computing the correlation between SABI and the Social Security Register finding a high correlation around 0.90 (Jofre et al. 2014).

Table 1. *Creative Service Industries by knowledge bases (NACE Rev. 2 codes)*

Code	Symbolic CSI	Code	Synthetic CSI	Code	Analytical CSI
58	Publishing	5821	Publishing of computer games	721	Scientific research and development
59	Audiovisual	5829	Other software publishing	722	Research and experimental development on social sciences and humanities
60	Programming and broadcasting	6201	Computer programming activities		
73	Advertising	6202	Computer consultancy activities		
7410	Design	7111	Architectural activities		
7420	Professional photography	7112	Engineering activities and related technical consultancy		
90	Arts				
91	Heritage				

Source: Elaborated from UNCTAD (2010) and following Asheim and Hansen (2009) classification of knowledge bases

I create 5 different samples. The first two are for CSI and Non-CSI firms in order to compare them. The following ones allow me to distinguish between the three different knowledge-bases of CIs – analytical, synthetic and symbolic –. I obtained these samples after excluding data of those firms that opened and closed in the same year, and those ones for which geographical coordinates are not available, leaving only active firms through all the period (2006 - 2015). Moreover, I drop all observations for which value-added, employees, intermediate materials and capital data are missing, negative or null. Finally, I deflate all monetary variables by industrial-level and consumption price indexes provided by IDESCAT (2011).

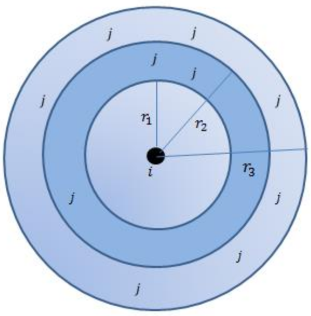
4.1. The variables

Table 2 summarises all variables definitions and sources. All variables employed in this work can be classified by categories: TFP variables for the first step in the empirical approach; and for the second step we use variables controlling for firm characteristics and local characteristics, as well as key variables capturing localisation and urbanisation economies.

Firm value-added, employees, intermediate inputs and capital (measured at the beginning of the year) are directly taken from the SABI database, as well as variables aiming to control for firm characteristics are size in terms of number of employees and type of firm in terms of capital. However, local agglomeration economies variables require more elaboration.

For each CSI, I construct a set of concentric ring firm variables, each of which measures the number of firms in CSI *j* present at a given distance (*r*) from the firm of reference *i* (see Figure 2). They can be understood as a measure of access of that firm to nearby neighbour firms (SCI firms for capture localisation economies and Non-SCI firms for urbanisation economies) in each year from 2006 to 2015 located in the city of Barcelona. I define three rings moving out in increments of 250 metres and then the following three rings moving out in increments of 500 metres, based on the coordinates of each firm as a reference: 0 to 250 metres, 250 to 500 metres, and 500 to 1000 metres. I also experiment with other ring divisions, but bearing in mind previous works analysing the attenuation of networking spillovers for advertising agencies in Manhattan (Arzaghi and Henderson 2008) and the spatial extent of agglomeration and coagglomeration for CIs in Barcelona (Coll-Martínez et al. 2016), CIs seem to only benefit from localisation economies within the first kilometre. Thus, taking into account these findings I expect to capture the effect of both localisation and urbanisation economies by using these ring divisions.

Figure 2. *Creating density rings to capture agglomeration economies*



Source: Author

Regarding the rest of local characteristics, the number of amenities by neighbour is also build by using GIS contour fitting routine to infer amenities for all firms on the dataset in Barcelona. They allow me to distinguish between different kinds of cultural amenities so associated to this CSI: cultural heritage, museums, natural amenities, research institutions, and art factories. Population density is directly taken from census data and it is considered to capture this demand potential of the city centre.

Table 3 shows usual descriptive statistics for my sample of symbolic-based CSI in Barcelona between 2006 and 2015 on which I will focus most of the empirical analysis.

Table 2. *Description of variables and sources*

Variable	Definition	Source
TFP variables		
VA	Value-Added (Ln).	SABI database (2006 - 2015)
L	Number of employees (Ln).	SABI database (2006 - 2015)
K	Total assets (Ln).	SABI database (2006 - 2015)
age	Firm age in years defined as the difference between the year of creation and the last data available on the database (Ln).	Own elaboration with SABI database (2006 - 2015)
M	Intermediate materials (Ln).	SABI database (2006 - 2015)
TFP	Total Factor Productivity estimated by using Ackerberg-Caves-Frazer Method (Ln).	Own elaboration with SABI database (2006 - 2015)
Firm Characteristics		
size	It indicates if the firm is a micro firm (1) (less than 10 employees), a small firm (2) (11 - 50 employees), a medium firm (3) (51 - 250 employees); or a large firm (4) (more than 251 employees).	Own elaboration with SABI database (2006 - 2015)
firm_type	Dummy variable taking value (0) if it is a Joint-stock company or (1) for a Limited Company.	Own elaboration with SABI database (2006 - 2015)
Localisation economies		
Intra_CSI_0-250	Count of symbolic-based CSI within a ring of 250 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Intra_CSI_250-500	Count of symbolic-based CSI within a ring between 250 and 500 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Intra_CSI_500-1000	Count of symbolic-based CSI within a ring between 500 and 1000 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Urbanisation economies		
Inter_NonCSI_0-250	Count of Non-CIs within a ring of 250 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Inter_NonCSI_250-500	Count of Non-CIs within a ring between 250 and 500 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Inter_NonCSI_500-1000	Count of Non-CIs within a ring between 500 and 750 metres from the firm of reference (Ln).	Own elaboration with SABI database (2006 - 2015)
Local characteristics		
Pop_density	Population density by district – inhabitants by km^2 (Ln).	Own elaboration with Departament d'Estadística de l'Ajuntament de Barcelona data (2006-2015)
Cultural_heritage	Number of cultural monuments by district (Ln).	Own elaboration with http://meet.barcelona.cat/ data (2006-2015)
Museums	Number of museums by district (Ln).	Own elaboration with http://meet.barcelona.cat/ data (2006-2015)
Natural amenities	Number of natural amenities such as public parks or beaches by district (Ln).	Own elaboration with http://meet.barcelona.cat/ data (2006-2015)
Research	Number of scientific or specialised training centres by district (Ln).	Own elaboration with http://meet.barcelona.cat/ data (2006-2015)
Art factories	Number of art factories by district (Ln).	Own elaboration with http://meet.barcelona.cat/ data (2006-2015)

Source: Own elaboration.

Table 3. *Descriptive statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
VA	180,228	5.34	1.55	0.01	15.03
L	180,228	2.00	1.12	0.69	10.22
K	180,228	6.19	1.75	0.00	17.42
age	180,228	2.81	0.58	1.10	4.75
M	180,228	5.18	2.14	0.00	15.90
ln_TFP1	176,403	0.56	0.53	-9.09	2.08
size	173,472	1.34	0.61	1.00	4.00
firm_type	180,017	1.82	0.38	1.00	2.00
Intra_CSI_0-250	166,118	2.99	1.21	0.00	5.15
Intra_CSI_250-500	166,118	3.94	1.32	0.00	5.77
Intra_CSI_500-1000	166,118	5.29	1.36	0.00	7.33
Inter_NonCSI_0-250	166,118	4.72	1.26	0.00	7.12
Inter_NonCSI_250-500	166,118	5.69	1.34	0.00	7.67
Inter_NonCSI_500-1000	166,118	6.99	1.31	0.00	8.67
Intra_symbolic_0-250	166,118	2.58	1.20	0.00	4.85
Intra_symbolic_250-500	166,118	3.51	1.31	0.00	5.49
Intra_symbolic_500-1000	166,118	4.77	1.35	0.00	6.39
Intra_symbolic_0-250	166,118	2.17	1.08	0.00	4.44
Intra_synthetic_250-500	166,118	3.07	1.23	0.00	4.90
Intra_synthetic_500-1000	166,118	4.33	1.25	0.00	5.79
Intra_analytical_0-250	166,118	0.61	0.90	0.00	4.78
Intra_analytical_250-500	166,118	1.12	1.13	0.00	5.44
Intra_analytical_500-1000	166,118	2.06	1.32	0.00	6.36
pop_density	180,228	3.79	2.06	0.07	10.48
cultural_heritage	180,228	2.00	0.39	1.39	2.94
museums	180,228	0.97	0.60	0.00	1.61
natural_amenities	180,228	1.43	0.61	0.00	2.20
art_factories	180,228	0.28	0.49	0.00	1.61

Source: Own elaboration. All variables are in expressed in natural logarithms, except for firm-type and size.

5. RESULTS

Here preliminary results are shown. First, I compare the results for all CSI to those of Non-CSI and later those ones for three different knowledge-bases (symbolic, synthetic and analytic). The main objective is to check the intensity and attenuation of agglomeration economies on firms' performance taking into account other factors that can determine their productivity.

5.1. Estimating the attenuation of agglomeration economies on CSI and Non-CSI firms' performance

Table 4 allows me to compare the results for CSI and Non-CSI. As stated in Section 3, all explanatory variables in the model are potentially correlated with omitted time-invariant variables. To cope with this issue I use three different approaches. First I add sector, neighbourhood, time and sectoral trend fixed effects to the robust OLS regression for panel data, then I estimate the same model by FE with and without introducing IV.

For CSI, coefficients for the dimension of firms indicate that there are not improvements of TFP when the size of firms increases TFP. However, those limited capital firms lead to better TFP results. I guess that these control variables may capture the effect of age, rather than a dimension effect. In other words, the younger firms, being also the smaller, are more efficient because they just come with innovative proposals of business.[8] Regarding localisation economies, their attenuation is not confirmed by the stock of CSI firms in the rings I defined. Moreover, urbanisation economies also do not present significant coefficients, but for the case of a significant positive effect in the second ring. I guess that these results are due to the different specificities among CSI sectors. They also suggest checking for the approach in which they are estimated. Population density as a proxy for demand has non-significant effects on CSI firms' productivity. Concerning urban amenities, I obtain mostly positive but non-significant results (i.e., cultural heritage, natural amenities and art factories); however I obtain a negative and significant coefficient for museums. This result may be explained by the fact that having more museums near could involve some congestion effects in terms of tourists, for instance. While for Non-CSI I obtain the same results for firm characteristics variables, results for agglomeration economies significantly vary. We obtain significant effects for the first ring of workers in CSI (see column 5) and also positive significant effects for Non-CSI rings at short distances. Population density seems to have negative effects on firms' productivity indicating possible disagglomeration effects, even they are not significant. Urban amenities are still mostly positive and significant. Even all that, results do not seem to be so robust when comparing the different approaches, then more work in this direction is needed.

[8] We do not take into account the age as a firm specific characteristic as it has been included on the first step to infer TFP.

Table 4. *Results for CSI and Non-CSI*

Dep. var.: Ackerberg et al. TFP	CSI			Non-CSI		
Model	(1) OLS	(2) FE	(3) IV	(4) OLS	(5) FE	(6) IV
Size						
Small	-0.256***	-0.222***	-0.224***	-0.344***	-0.351***	-0.350***
	(0.0124)	(0.0203)	(0.0205)	(0.00679)	(0.0119)	(0.0119)
Medium	-0.994***	-0.612***	-0.609***	-1.207***	-1.102***	-1.100***
	(0.0532)	(0.0854)	(0.0851)	(0.0274)	(0.0525)	(0.0527)
Large	-2.085***	-1.148***	-1.144***	-2.157***	-1.949***	-1.948***
	(0.159)	(0.195)	(0.196)	(0.135)	(0.148)	(0.148)
Limited Company	0.0794***	-	-	0.0259**	-	-
	(0.0195)			(0.0106)		
Intra_CSI_0-250	0.00347	-0.00741	-0.00904	-0.00814	0.0286*	0.0209
	(0.0169)	(0.0356)	(0.0364)	(0.00917)	(0.0169)	(0.0187)
Intra_ CSI_250-500	-0.0274	-0.0316	-0.0456	0.0189	0.0228	0.00984
	(0.0231)	(0.0570)	(0.0629)	(0.0133)	(0.0252)	(0.0290)
Intra_ CSI_500-1000	-0.0696*	0.0248*	0.00899	0.00744	0.0431***	0.0310***
	(0.0402)	(0.0137)	(0.0163)	(0.0171)	(0.00734)	(0.00949)
Inter_ NonCSI_0-250	0.0108	0.0233	0.0264	0.0195**	-0.0147	-0.0177
	(0.0192)	(0.0733)	(0.0721)	(0.00973)	(0.0378)	(0.0389)
Inter_ NonCSI_250-500	0.0571**	0.0454	0.0362	-0.0332**	-0.0300	-0.0589
	(0.0268)	(0.0975)	(0.102)	(0.0145)	(0.0512)	(0.0639)
Inter_ NonCSI_500-1000	0.00619	0.136	-	0.00280	0.0815	-
	(0.0386)	(0.156)		(0.0185)	(0.0693)	
pop_density	-0.0140	-0.00741	-0.00904	-0.00863	0.00964	0.00699
	(0.0158)	(0.0356)	(0.0364)	(0.00733)	(0.00680)	(0.00565)
cultural_heritage	0.192	-	-	-0.0368	-	-
	(0.123)			(0.0754)		
museums	-0.0233	-	-	0.216***	-	-
	(0.120)			(0.0430)		
natural_amenities	0.0292	-	-	-0.0695	-	-
	(0.0853)			(0.0673)	-	-
art_factories	0.0129	-0.0153	-0.0163	0.0213*	0.0535***	0.0502***
	(0.0260)	(0.0235)	(0.0234)	(0.0125)	(0.0108)	(0.0110)
Sector FE	Yes	-	-	Yes	-	-
Time FE	Yes	-	-	Yes	-	-
Neighbourhood FE	Yes	-	-	Yes	-	-
Constant	0.0160	-0.595	0.333	0.437*	-0.0849	0.676*
	(0.300)	(0.939)	(0.638)	(0.239)	(0.445)	(0.410)
Num. firms	2,895	2,895	2,895	10,095	10,095	10,095
N	17,503	17,503	17,503	60,735	60,735	60,735
R^2	0.288	0.036	-	0.400	0.083	-

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Own elaboration. All explanatory variables are lagged one period except for size and firm type. Columns (3) and (6) show results for a fixed effects instrumented model. Population density is instrumented by the distance to Barcelona commercial and social centre (Plaça Catalunya), the number of housing units in 1990 and historical population of Barcelona in 1900, all of them in natural logarithms.

5.2. Estimating the attenuation of agglomeration economies on different knowledge-based CSI firms' performance

As we have seen in previous regressions for all CSI firms, my expectations about finding out a clear attenuation and intensity of localisation economies have not been confirmed, applying the same analysis to each knowledge-based CSI industries could help to clarify this evidence as they are supposed to clearly benefit from networking and face-to-face interaction. In this case, I add time and neighbourhood fixed effects to the robust OLS regression for panel data. Results are presented in Table 5.

For all three types of knowledge bases coefficients for firms' characteristics indicate that there are not improvements of TFP when the size of firms increases TFP. However for synthetic and analytical based firms I still cannot confirm my hypothesis, then I will focus on analyse Column (1). Unlike in previous results, increasing by 10% the number of symbolic-based firms within the first 250 metres from the firm, keeping the size of other sectors in the area constant, increases the TFP of a symbolic-based firm by 0.36%. Yet, this effect turns to be negative and significant by 500 and 1000 metres. This result is consistent with Arzaghi and Henderson (2008) results for advertising agencies in Manhattan. In this sense, any inferred networking effects end at ring 2, upholding the hypothesis on the critical role of spatial proximity for benefiting from networking effects. Interactions in symbolic-based CSI occur primarily within 250 metres, that is, a 10 minutes journey of walking during the day within Barcelona with its crowded conditions. Urbanisation economies seem to positively affect the TFP of symbolic-based firms, which seems to benefit for diversity of activities. Concerning local characteristics, population density as a proxy to expected demand is not significant. Finally, may aim to capture the effect of urban amenities enhancing the networking of creative professionals by the different cultural amenities variables seems not to fully capture the effects of these factors to TFP. Probably, this variable is too much generic and more specific amenities should be taken into account to infer the effects of agglomeration economies on TFP from those ones of amenities and soft characteristics.

All in all, these preliminary results do not allow me to confirm that for CSI the spatial extent of agglomeration economies. However, they provide evidence on that for those CSI more relying of networking and face-to-face interaction – i.e., symbolic-based activities – benefit from localisation economies at short distances and that this localisation effects rapidly decay with distance.

5.3. Robustness checks

In this section we summarise the main results for CSI and symbolic-based CSI in a sequential way in order to check the robustness of the model.

Table A2 (Annex) shows the results for all CSI. For CSI I find significant localisation economies between 0 and 250 metres, but this effect disappears when urbanisation economies variables are added (column 3). When adding sector, time and neighbourhood fixed effects the marginal increase in the goodness of fit is redundant.

Regarding symbolic-based CSI, Table A3 (Annex) depicts their results. In this case, there localisation effects at reduced distance (0-250 metres) seem to be more robust, since it remains positive and significant in all columns. Nevertheless, sector, time and neighbourhood fixed effects provides the marginal increase in the goodness of fit is redundant.

Table 5. *Results for different knowledge-based CSI*

Dep. var.:	Ackerberg et al. TFP		
Model	(1) Symbolic	(2) Synthetic	(3) Analytical
Size			
Small	-0.271***	-0.269***	-0.268***
	(0.0172)	(0.0172)	(0.0172)
Medium	-1.013***	-1.010***	-1.006***
	(0.0676)	(0.0671)	(0.0669)
Large	-1.965***	-1.954***	-1.943***
	(0.177)	(0.176)	(0.175)
Limited Company	0.0832***	0.0804***	0.0799***
	(0.0254)	(0.0256)	(0.0255)
Intra_$_0-250 [a]	0.0356*	-0.0295	-0.00564
	(0.0203)	(0.0192)	(0.0121)
Intra_$_250-500	-0.0430	-0.0533**	0.0142
	(0.0303)	(0.0258)	(0.0144)
Intra_$_500-1000	-0.138**	-0.0212	-0.0171
	(0.0565)	(0.0470)	(0.0197)
Inter_NonCSI_0-250	-0.0266	0.0156	-0.00536
	(0.0276)	(0.0272)	(0.0245)
Inter_NonCSI_250-500	0.105***	0.115***	0.0690**
	(0.0401)	(0.0392)	(0.0342)
Inter_ NonCSI_500-1000	0.0608	-0.0463	-0.0590
	(0.0608)	(0.0504)	(0.0377)
pop_density	-0.00253	-0.000680	-0.000823
	(0.0177)	(0.0177)	(0.0177)
cultural_heritage	0.121	0.0841	0.0552
	(0.134)	(0.128)	(0.127)
museums	0.127*	0.0914	0.107
	(0.0729)	(0.0700)	(0.0714)
natural_amenities	-0.119*	-0.0669	-0.0829
	(0.0681)	(0.0705)	(0.0704)
art_factories	0.0339	0.0324	0.0268
	(0.0330)	(0.0331)	(0.0331)
Time FE	Yes	Yes	Yes
Neighbourhood FE	Yes	Yes	Yes
Constant	-0.0518	0.122	0.433
	(0.401)	(0.390)	(0.358)
Num. firms	1,911	1,911	1,911
N	11,533	11,533	11,533
R^2	0.276	0.275	0.275

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

[a] *These variables change for each kind of knowledge base.*

Source: Own elaboration. All explanatory variables are lagged one period except for size and firm type.

6. CONCLUSIONS

The aim of this paper was to infer the spatial extent of agglomeration economies for the CIs in Barcelona and its relationship with creative firms' performance. Using micro-geographic data of firms between 2006 and 2015 I estimate the effect of intra-industry agglomeration (CSI) in rings around location on productivity in Barcelona. Main results are that, (1) for CSI, at a micro-spatial level, localisation economies are not so relevant, although much work still remains to be done on this issue; (2) while for Non-SCI having creative workers in the near proximity (250 metres) seems to enhance their productivity; and (3) for the symbolic-based CSI localisation economies – mainly understood as networking and knowledge externalities – have positive effects on TFP at shorter distances (less than 250 metres), while for the two other knowledge-based CSI (i.e., synthetic and analytical) localisation economies seem not to be so relevant.

These results suggest the importance of networking or information spillover effects for some creative activities, such as advertising agencies, which are highly concentrated in the largest cities. Such benefits may differ across each CSI, even the intrinsic characteristics they share, suggesting the strong specificities arising among them that policy makers should take into account when designing urban regeneration policies.

Future research will focus on improving the estimation of the models proposed; concretely, the use of alternative instrumental variables and other panel data estimation approaches could help coping with endogeneity and simultaneity issues. Moreover, I will expand this work by analysing the interaction and simultaneity effects between the productivity of CSI and Non-CSI. Finally, the creation of other variables proxying cultural and social interaction areas will allow taking into account most specific factors leading to the agglomeration of creative activities.

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Annex

Table A1. *Temporal composition of the number of firms by category*

Year	SCIs	Non SCIs	Analytical	Synthetic	Symbolic	Advertising
2006	4003	24331	79	1526	2707	1137
2007	4206	25408	94	1623	2802	1166
2008	4398	26090	108	1729	2875	1200
2009	4432	26067	106	1777	2865	1207
2010	4414	26096	118	1793	2806	1179
2011	4381	25986	125	1781	2774	1169
2012	4323	25813	132	1776	2702	1155
2013	4307	25676	128	1784	2680	1168
2014	4314	25298	121	1796	2685	1183
2015	4103	23553	112	1707	2547	1108

Source: Own elaboration with SABI's database.

Table A2. *Robust OLS with fixed effects for CSIs*

Dep. var.:	Ackerberg et al. TFP							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size								
Small	-0.254***	-0.255***	-0.258***	-0.258***	-0.258***	-0.257***	-0.255***	-0.256***
	(0.0121)	(0.0124)	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0124)
Medium	-0.990***	-0.992***	-0.994***	-0.995***	-0.993***	-0.992***	-0.991***	-0.994***
	(0.0525)	(0.0544)	(0.0545)	(0.0545)	(0.0544)	(0.0539)	(0.0538)	(0.0532)
Large	-2.062***	-2.073***	-2.078***	-2.079***	-2.089***	-2.081***	-2.078***	-2.085***
	(0.155)	(0.158)	(0.158)	(0.158)	(0.158)	(0.159)	(0.160)	(0.159)
Limited Company	0.0783***	0.0842***	0.0834***	0.0839***	0.0832***	0.0776***	0.0768***	0.0794***
	(0.0192)	(0.0196)	(0.0196)	(0.0196)	(0.0195)	(0.0198)	(0.0198)	(0.0195)
Intra_CSI_0-250		0.0311***	0.0177	0.0163	0.0143	0.0163	0.0190	0.00347
		(0.0111)	(0.0153)	(0.0153)	(0.0153)	(0.0151)	(0.0153)	(0.0169)
Intra_CSI_250-500		0.00180	-0.0114	-0.0124	-0.0122	-0.0166	-0.00717	-0.0274
		(0.0127)	(0.0166)	(0.0166)	(0.0177)	(0.0177)	(0.0194)	(0.0231)
Intra_CSI_500-1000		-0.0165	0.0336***	0.0355***	0.0359***	0.0378***	0.00874	-0.0696*
		(0.0107)	(0.0117)	(0.0116)	(0.0115)	(0.0113)	(0.0276)	(0.0402)
Inter_Non-CSI_0-250			0.0215	0.0205	0.0255	0.0162	0.0112	0.0108
			(0.0177)	(0.0176)	(0.0178)	(0.0178)	(0.0181)	(0.0192)
Inter_Non-CSI_250-500			0.0434*	0.0446*	0.0444*	0.0474**	0.0436*	0.0571**
			(0.0237)	(0.0235)	(0.0234)	(0.0235)	(0.0240)	(0.0268)
Inter_Non-CSI_500-1000			-0.0931***	-0.0906***	-0.0845***	-0.0814***	-0.0592**	0.00619
			(0.0177)	(0.0181)	(0.0199)	(0.0201)	(0.0289)	(0.0386)
pop_density				-0.0105	-0.0100	-0.00841	-0.00896	-0.0140
				(0.0110)	(0.0114)	(0.0114)	(0.0116)	(0.0158)
cultural_heritage					0.0453*	0.0399*	0.0316	0.192
					(0.0235)	(0.0232)	(0.0232)	(0.123)
museums					-0.0402***	-0.0341***	-0.0287**	-0.0233
					(0.0130)	(0.0129)	(0.0132)	(0.120)
natural_amenities					0.0318**	0.0259*	0.0229	0.0292
					(0.0147)	(0.0146)	(0.0145)	(0.0853)
art_factories					0.0327**	0.0294*	0.0236	0.0129
					(0.0165)	(0.0164)	(0.0169)	(0.0260)
Sector FE	No	No	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	Yes	Yes
Neighbourhood FE	No	No	No	No	No	No	No	Yes
Constant	0.684***	0.662***	0.795***	0.807***	0.637***	0.521***	0.498***	0.0160
	(0.0191)	(0.0355)	(0.0526)	(0.0543)	(0.0898)	(0.126)	(0.126)	(0.300)
Num. firms	3,076	2,892	2,892	2,892	2,892	2,892	2,892	2,892
N	19,302	14,366	14,366	14,366	14,366	14,366	14,366	14,366
R^2	0.255	0.270	0.273	0.273	0.274	0.280	0.282	0.288

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*
Source: Own elaboration.

Table A3. *Robust OLS with fixed effects for Symbolic-based CSI*

Dep. var.:	Ackerberg et al. TFP							
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size								
Small	-0.263***	-0.275***	-0.276***	-0.277***	-0.275***	-0.273***	-0.271***	-0.272***
	(0.0172)	(0.0176)	(0.0175)	(0.0174)	(0.0173)	(0.0171)	(0.0171)	(0.0172)
Medium	-1.021***	-1.022***	-1.018***	-1.019***	-1.015***	-1.012***	-1.011***	-1.010***
	(0.0667)	(0.0695)	(0.0692)	(0.0691)	(0.0691)	(0.0684)	(0.0682)	(0.0676)
Large	-1.936***	-1.948***	-1.955***	-1.952***	-1.971***	-1.962***	-1.955***	-1.966***
	(0.170)	(0.176)	(0.177)	(0.176)	(0.180)	(0.178)	(0.177)	(0.177)
Limited Company	0.0757***	0.0859***	0.0863***	0.0871***	0.0874***	0.0807***	0.0790***	0.0837***
	(0.0251)	(0.0255)	(0.0254)	(0.0255)	(0.0253)	(0.0259)	(0.0258)	(0.0253)
Intra_symbolic_0-250		0.0532***	0.0445**	0.0421**	0.0331*	0.0333*	0.0335*	0.0532***
		(0.0155)	(0.0189)	(0.0188)	(0.0187)	(0.0184)	(0.0184)	(0.0155)
Intra_symbolic_250-500		0.0260	-0.00858	-0.0111	-0.0103	-0.0121	-0.0104	0.0260
		(0.0194)	(0.0243)	(0.0243)	(0.0246)	(0.0244)	(0.0243)	(0.0194)
Intra_symbolic_500-1000		-0.0561***	-0.0370	-0.0337	-0.0201	-0.0197	-0.0123	-0.0561***
		(0.0177)	(0.0325)	(0.0326)	(0.0328)	(0.0324)	(0.0324)	(0.0177)
Inter_ Non-CSI_0-250			0.00722	0.00528	0.0154	0.00899	0.00786	0.00864
			(0.0220)	(0.0219)	(0.0217)	(0.0218)	(0.0218)	(0.0245)
Inter_ Non-CSI_250-500			0.0522*	0.0537*	0.0552*	0.0575**	0.0575**	0.0814**
			(0.0294)	(0.0293)	(0.0289)	(0.0291)	(0.0290)	(0.0344)
Inter_ Non-CSI_500-1000			-0.0379	-0.0322	-0.0311	-0.0315	-0.0423	0.0710
			(0.0323)	(0.0327)	(0.0345)	(0.0344)	(0.0345)	(0.0555)
pop_density				-0.0180	-0.0191	-0.0150	-0.0167	-0.00136
				(0.0136)	(0.0141)	(0.0142)	(0.0142)	(0.0176)
cultural_heritage					0.0707**	0.0651**	0.0587**	0.119
					(0.0302)	(0.0300)	(0.0299)	(0.133)
museums					-0.0699***	-0.0616***	-0.0583***	0.103
					(0.0181)	(0.0180)	(0.0179)	(0.0727)
natural_amenities					0.0490**	0.0420**	0.0408**	-0.106
					(0.0191)	(0.0190)	(0.0189)	(0.0725)
art_factories					0.0632***	0.0589***	0.0423*	0.0333
					(0.0206)	(0.0206)	(0.0217)	(0.0329)
Sector FE	No	No	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	Yes	Yes
Neighbourhood FE	No	No	No	No	No	No	No	Yes
Constant	0.682***	0.714***	0.446**	0.441**	0.378	0.456*	0.547**	-0.281
	(0.0249)	(0.0661)	(0.207)	(0.207)	(0.252)	(0.259)	(0.268)	(0.613)
Num. firms	2,017	1,910	1,910	1,910	1,910	1,910	1,910	1,910
N	12,648	9,526	9,526	9,526	9,526	9,526	9,526	9,526
R^2	0.240	0.255	0.256	0.257	0.260	0.266	0.268	0.276

*Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*
Source: Own elaboration.