Title:

Place the 'Candy' and 'Crush' it: Entry determinants of the Software and Video games firms in Barcelona

Author and e-mail: Carles Méndez-Ortega (carles.mendez@urv.cat)

Department: Department of Economics, QURE and CREIP

University: Universitat Rovira i Virgili

Subject Area: S01 - Geografía de las Industrias Creativas: ¿Por qué se clusterizan?

Abstract: *This paper aims to determine which reasons lead Software and Video games firms (SVE hereafter) to locate in certain areas of Barcelona. This high-tech industry is a key industry in developed economies mainly located in urban areas. To carry out this analysis, we use SVE firm entries at neighbourhood level between 2011 and 2013 and a set of covariates that capture neighbourhood characteristics (localization and agglomeration economies, high-tech amenities, diversity, human capital and crime). Our results show that i) SVE firms tend to choose locations with a high diversity and good high-tech amenities (e.g. 22@ district in Barcelona), ii) the importance of the localization and agglomeration economies, since spatial spillovers are a key factor for this type of firms and iii) the role of the diversity in the location process of these firms, since SVE firms choose places with a high diversity of cultural and creative activity.*

Keywords: Software and Video games Industry, location determinants, Count Data models, Barcelona

JEL Codes: R10, R30, L86

1. INTRODUCTION

In recent decades, the Technological Revolution has changed the way in which people interrelate, communicate and work. This revolution has prompted the emergence and rise of high-tech industries, considered the key drivers behind economic growth in developed countries due to their capacity for knowledge generation, creativity and innovation (Berger and Frey, 2016). One of the most important high-tech industries, which has a huge impact on the economy and economic growth and which is analyzed in this study, is the software and video games industry (SVE hereafter).

There are many ways to define software but, in general terms, software is a set of instructions, information and/or programs that are given to a computer to do specific tasks. So, the SVE industry covers a wide variety of firms: for example, software development firms, software management firms and video games firms (companies that combine software development with a more creative component in order to create electronic entertainment games).

The impact of this industry in the current world economy is huge and it is constantly growing. Indeed, in 2014, the total contribution of this industry in terms of GDP to the economy of the European Union (EU) was more than 900 billion euros (7.9% of the EU28 GDP). In the same year, the industry generated more than 11.6 million jobs (5.3% of the EU28 jobs), of which 3.1 million were direct jobs. The wages in this industry are considerably higher than in other industries (e.g. the EU average wage for the software industry is 34% higher than the EU average wage and 80% higher than the average wage in the services sector). This is because it is a highly qualified industry with highly skilled workers. In Spain, the total contribution of this industry to the GDP is more than 35,800 million euros (3.4% of the Spanish GDP) and more than 624 thousand jobs are SVE-industry related (219 thousand direct and 405 thousand indirect jobs) (BSA & The Economist Intelligence Unit, 2016). The sector has 360 thousand employees (whose average salary is over 30 thousand euros per year) and adds 30 billion euros of gross output to the Spanish economy (INE, 2016). However, the impact of the SVE industry is greater and more far reaching than economic indicators suggest, since its technology is a part of almost all economic sectors.

The SVE industry belongs to the Information and Communication Technologies industry (commonly known as ICT) and is regarded as a creative industry (Boix and Lazzeretti, 2012). Creative industries are economic activities that are closely linked to the generation of knowledge (i.e. advertising, crafts, fashion, film and music, among others) (Howkins, 2001). In these industries, human capital plays a crucial role, since it is the main input and can make the difference between the success and failure of economic activity. The location patterns of creative firms have been an interesting topic for researchers because creative firms are an important factor in local economic growth and development (Coll-Martínez et al., 2019). Also, the emergence of creative firms improves the competitiveness and diversity of local economies (De Propris, 2013).

The SVE industry is mainly located in urban areas, since there are good infrastructures, good accessibility to amenities and a high level of human capital (i.e. more educated people). Therefore, these are environments in which information and contacts between firms flows easily. Due to the economic importance and economic growth of the industry, a large number of cities, as a strategy to attract this type of firms, have developed urban projects aiming to create technological districts (e.g. Méndez-Ortega and Arauzo-Carod, 2018, which discusses the 22@ district in Barcelona, the *Hafencity* district in Hamburg and the *Confluence* district in Lyon).

Most previous empirical research into location determinants of high-tech firms has been done at country and/or regional level, even though this industry is purely urban. For this reason, this paper contributes to the literature by providing an empirical study that analyzes the location determinants of the SVE industry at the urban level, and deals with factors that have not been taken into account, or have not been analyzed together on this scale (i.e. traditional factors such as agglomeration economies, human capital and amenities; social factors such as cultural and creative diversity; and crime factors, widely used in US studies but not in European studies).

Our main results show that at the city level, SVE firms tend to choose locations with a high diversity of creative firms, social amenities and high-tech amenities (*e.g*. the 22@ district in Barcelona). They also show the importance of agglomeration economies: SVE firms choose locations with a large number of well-established SVE firms, which shows the importance of spatial spillovers for this type of firm.

The rest of the paper is organized as follows. Section 2 reviews the theoretical and empirical literature about the location determinants of SVE firms. Section 3 describes the data and the econometric methodology. Section 4 introduces and discusses the main results. And finally section 5 presents the main conclusions.

2. LOCATION OF SOFTWARE AND VIDEO GAMES FIRMS AT THE INTRA-URBAN SCALE

Firm location determinants have been one of the most studied topics in Urban and Regional Economics since the seminal work by Marshall (1890), which explained the location of new plants in industrial districts. Since then and to this day, firms' location decisions have been both an important topic for academics from a variety of areas and a great topic of interest for firms, since optimal location means greater profit, market accessibility and, in general, can mark the difference between success and business failure.[1]

Throughout the 20th century, most research into industrial location, agglomeration and industrial patterns focused on theoretical issues, and the few empirical studies, there were mainly dealt with manufacturing industries. For a few years now, empirical studies on industrial location have been changing from manufacturing industries to high-tech industries, due to their interest for entrepreneurship and economic growth (Gilbert, 2017). Even greater interest is shown in the location and clustering of the Information and Communication Technology industries, which has been analyzed by large numbers of researchers in recent years because of their impact on every economic industry (Fernhaber et al., 2008; Giblin, 2011).

Most of these studies focused on location at the regional or country level, but less is known about the location determinants of these industries at the urban level, even though these industries are only located in urban contexts. The novel work by Jacobs (1969) and Lucas (1988) gave rise to urban theory, which proved that the greater economic performance of cities is due to the huge density of human capital. Hence, this type of industry has boosted the growth of large cities, since it has been observed that cities where there is a high endowment of human capital grow substantially more than those where this endowment is more restricted (Berger and Frey, 2016).

[1] An extensive empirical review on industrial location can be found in Arauzo-Carod et al., (2010).

Location determinants of software and video games firms

The spatial concentration of high-tech activities is an established fact in almost every developed city around the world. There is a lengthy body of literature which explains the nature and extent of urban agglomeration economies (for a survey, see Duranton and Puga, 2004; Rosenthal and Strange, 2004).

The intra-metropolitan location decision is essentially based on cost minimization and not firms' profit, since for high-tech activities consumer demand for output is assumed not to vary within intra-metropolitan locations (Gómez-Antonio and Sweeney, 2018). So, the cost function (*C*) for a firm selecting a location has been represented in the literature as the function[2]:

$$C = F(AE, G, HC, t, LP, S)$$

where *AE* are the agglomeration economies, *G* are the public services in the area (e.g. transport services, Wi-Fi public services, public centers, urban renewal areas made by public initiative, among others), *HC* is the human capital or skilled labor in the area, *t* and *LP* are the effective tax rate and land price and *S* is a vector of general site characteristics (i.e. covariates such as the presence of technology parks, universities, creative diversity, crime in the area and other site characteristics that affect high-tech firms' location). Numerous empirical studies have shown the impact of these variables on firms' location decisions (see below).

Several empirical studies have shown the positive impact of agglomeration economies as a location determinant for high-tech industries at the regional/country level (e.g. Audretsch and Lehmann, 2005 and Kinne and Resch, 2017, for the case of Germany or Frenkel, 2012, for the case of Israel, among others) or the metropolitan level (e.g. Arauzo-Carod and Viladecans-Marsal, 2009, for Barcelona, and Hackler, 2003, for a set of US metropolitan areas). The main reason that leads these firms to locate close to each other is to create networks, input and output linkages, and to improve product and process innovation (Lyons, 1995). This attraction seems to be more intense with such creative sectors as the video and film industries, advertising or radio and TV firms, because their activities are similar and connected (Méndez-Ortega and Arauzo-Carod, 2019).

[2] These covariates and specifications for high-tech firms' location are in line with the literature (see Brülhart et al., 2012 and Gómez-Antonio and Sweeney, 2018).

An important location determinant for SVE firms is the availability of good amenities. A city with a good allocation of high-tech amenities is a city that attracts a large number of SVE firms. One of the amenities that has been successful in attracting knowledge-based and high-tech firms are “techno-neighborhoods” (Duvivier and Polèse, 2017). These are places inside the city with a large number of resources for firms that facilitate interaction between them. One example is the success of the 22@ district in Barcelona, an urban renewal project promoted in Barcelona that aimed to attract high-tech firms (Viladecans-Marsal and Arauzo-Carod, 2012). Also worth noting are amenities such as Wi-Fi hotspots inside the city, since they can be a proxy of virtual vitality and, therefore, an indicator of urban vitality (Kim, 2018), contributing to the creation environments that generate knowledge.

Another significant factor for the location of SVE firms is cultural and creative diversity, since high-tech firms make location decisions based on where talented people are located. As Florida and Gates (2003) suggested, there is a connection between the level of tolerance of a metropolitan area, in conjunction with its ethnic, social and cultural diversity, and the attractiveness of the area for talented people in high-tech firms, which generates the emergence of this type of firm as an indicator of a metropolitan area’s high-technology success. So, as empirical evidence suggests, places with considerable creative diversity and a good social environment (i.e. tolerance and talent) are places where high-tech and knowledge-intensive firms will be located (Yamamura and Goto, 2018; Zandiatashbar and Hamidi, 2018).

As mentioned above, human capital is a basic and strategic input for SVE firms. For this reason, the role of higher education providers (i.e. universities, research centers and tertiary education institutions) in the training of human capital is fundamental. Cities that are active in education tend to have a large share of highly educated workers (Abel and Deitz, 2012). These institutions have an impact not only on human capital formation, but also on the generation of knowledge, R&D activities, innovation processes and externalities. This explains the location of new firms close to these institutions, since university spillovers are important for high-tech firms (Acosta et al., 2011) and R&D firms in general (Abramovsky and Simpson, 2011).

Other significant factors are the rental prices and taxes. Generally, firms will choose locations where prices and taxes are lower. Some empirical studies show that prices and taxes have a negative effect on the location of high-tech firms (e.g. Acosta et al., 2011 and Wang et al., 2017; among others). Nevertheless, in a city, taxes are constant and the effect of land price tends to be captured by other variables, as Figueiredo et al. (2002) suggested (*e.g.* agglomeration economies).

Finally, crime is a determinant to be taken into account, since it is proven that it affects the location of high-tech activity (Goetz and Rupasingha, 2002; Hackler, 2003). Unfortunately, this variable is used more often in US studies than in European studies, because in Europe there is not such an established tradition of collecting crime data.

Thus, now that we have seen the main location determinants of SVE firms, we present a set of empirical studies which discuss what determines a high-tech or knowledge base firm's location choices (see Table 1).

[INSERT TABLE 1]

Each of the studies analyzes some of the determinants discussed above. However, none of them analyze them all at the same time and at the urban scale. Therefore, this paper analyzes all these determinants as a whole, and gives a more accurate vision of what determines the location of SVE firms within the city. Along these lines, at the urban level we expect the following:

> Hypothesis 1: *The impact of High-tech amenities, Cultural and Creative Diversity and Human Capital will have a positive impact on SVE firm entries while these impacts will be different across types of entry (i.e. Creative and All entries). The impact of High-tech amenities and Human Capital will be higher for SVE firm entries than for Creative and All firm entries.*

Amenities are expected to be important for this industry (Li and Zhu, 2017; Woodward et al., 2006), as is cultural diversity (Florida and Gates, 2003) and this impact will depend on the type of firm (SVE firms, Creative firms and All firms). Also, we expect that:

> Hypothesis 2: *The impact of Agglomeration economies, High-tech amenities, Human Capital, Creative and Cultural Diversity and Crime on SVE firm entries will go beyond neighborhood borders.*

Space for industrial location is one of the most important issues. Empirical evidence has shown that the location of new economic activity is connected to space (see Liviano and Arauzo-Carod, 2012, for an extensive discussion on the importance of space for the location of new economic activity). This hypothesis is raised because firm location and space has been subject to a considerable amount of analysis at country, regional and municipality level but not at the urban level, which we expect to have an impact on SVE firm entries.

3. DATA AND METHODOLOGY

3.1 Study area and datasets

This empirical analysis focuses on the location of the software and video games firms in the city of Barcelona at the neighborhood level. This city is the second biggest city in Spain in terms of population (1.6 million inhabitants in 2016) and has a surface area of 101.9 km^2.[3] Due to sea and mountain restrictions, it is a densely populated city (more than 15,800 inhabitants per km^2). The city is divided into 10 districts and 73 neighborhoods (see Figure 1).

[INSERT FIGURE 1]

To carry out this analysis, we used firm and city characteristic variables. The data on the firms from Barcelona city and their basic information (i.e. location and year of establishment) are taken from SABI[4] (Sistema de Análisis de Balances Ibéricos, INFORMA). The data on the neighborhoods is mainly taken from the Barcelona City Council's open data service (known as Open Data BCN). This database provides social, economic and demographic information about the city for several aggregation levels (city, district, neighborhood and census level).

To identify the SVE firms and other creative activities, we used the classification by UNCTAD (2010). This classification includes all creative industries (both manufacturing and service creative industries) and is widely accepted by researchers (see Boix and Lazzeretti, 2012; Méndez-Ortega and Arauzo-Carod, 2018).[5] Therefore, we include 17

[3] Our area of study is the city of Barcelona and not its metropolitan area (which includes 35 municipalities). This is because there is no information for some municipalities so an analysis at the metropolitan scale cannot be made. Nevertheless, the city of Barcelona accounts approximately for 80% of SVE firms in the metropolitan area.

[4] SABI is a database of firms that collects information from the Spanish Mercantile Register, where all limited liability companies and corporations are obliged by law to deposit their balance sheets. Due to its coverage SABI is the most widely used database in Spain when firm georeferenciation is required.

[5] A definition of each creative industry and their respective NACE codes can be found in the annex (Table A1.)

creative sectors (of which only SVE, Advertising, Video and film and Radio and TV firms will be treated individually, and the rest jointly)[6].

[INSERT TABLE 2]

Table 2 shows some descriptive statistics of the variables used in this paper. Selected variables are in line with the economic theory of location and with the empirical evidence of high-tech firm location determinants discussed in the previous section (Hackler, 2003; Kinne and Resch, 2017).

3.2 Methodology

Model specification

This empirical analysis focuses on software and video games firms in the city of Barcelona. Using the previous theoretical and empirical review on firm location, we estimate the number of new firms in a neighborhood as a function of specific neighborhood characteristics:

$$Firm\ entries_{i(2011-2013)} = \beta_0 + \beta_{1n}AE_{in} + \beta_{2k}HTA_{ik} + \beta_{3j}CCD_{ij} + \beta_{4h}HC_{ih} + \beta_5 Crime_i + \mu_i$$

where *Firm entries*$_{i(2011\text{-}2013)}$ is the number of firms located in neighborhood i between 2011 and 2013, AE_{in} are Agglomeration economies in neighborhood i where (n = 1,…,N) is the set of these variables, HTA_{ik} are High-tech amenities in neighborhood i where (k = 1,…,K) is the set of these variables, CCD_{ij} is Creative and Cultural diversity in neighborhood i where (j = 1,…,J) is the set of these variables, HC_{ih} is Human Capital in neighborhood i where (h = 1,…,H) is the set of these variables and $Crime_i$ is the number of police incidents in neighborhood i in 2010.[7]

To make a general comparison of firm entries, three different dependent variables were used (SVE firm entries, Creative firm entries and All firm entries).[8] This made it possible

---

[6] These industries were selected in accordance with Méndez-Ortega and Arauzo-Carod (2019) and are related to the SVE industry through their processes.

[7] Land costs are included in the neoclassical economic theory of location, but we did not include them in the empirical model, since taxes are the same across all neighborhoods and the land price effect is captured by other variables such as population density or agglomeration economies (Figueiredo et al., 2002). To test this, we found a positive and statistically significant effect of population density and education on rent prices in Barcelona (table A2.).

[8] The variable Creative firm entries does not include SVE firm entries and the variable All firm entries does not include Creative firm entries. We tried including them, but the results did not change (see Robustness checks section).

to check differences between entry determinants between industries and it gave more accurate information about the results, since the impact of selected covariates can be compared across industries.

Model selection

To ensure that the group of covariates would properly explain SVE firm location decisions, we included the variance inflation factor (VIF) and correlation diagnostics in our model. VIF provides an index of how much higher the variance is when covariates are correlated than when they are uncorrelated. There is a multicollinearity problem whenever this value is higher than 10. For our subsamples, all VIF values were below 3, so we rejected the possibility of a multicollinearity problem. Furthermore, we tested the covariate correlations and most potentially correlated variables had values around 0.[9]

The number of firm entries in an area is most commonly modeled with Count Data models (CDM) (Arauzo-Carod et al., 2010). CDMs represent the number of occurrences of an event within an area in a fixed period. These models include the Negative Binomial model (NBM), the Poisson model (PM), the Zero-Inflated Binomial Model (ZIBM) and the Zero-Inflated Poisson Model (ZIPM). To determine which models fitted our estimation, we used the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and the Vuong test as Cameron and Trivedi (2013) suggest.[10]

[INSERT TABLE 3]

Descriptive statistics of the dependent variables (see Table 3) suggested that there was not a problem of overdispersion or zero inflation. To test which model fitted best for each situation, we estimated a baseline specification for each case using CDM and applied the aforementioned selection tests (Table 4). These results determined that the PM performed best for SVE firm entry specification and NBM performed best for Creative and All firm entry specifications. Moreover, the Vuong test was not statistically significant, so we rejected zero-inflated models.

[9] See correlation table in the annex (table A3.).

[10] AIC and BIC are standard measures to test which model best fits the data. The model with the lowest AIC and BIC value is preferred to the rest of the models. The Vuong test (Vuong, 1989) tests the significance of a zero-inflated model compared to a non-zero inflated model in terms of a significant difference from zero in the overdispersion parameter. So, a positive and statistically significant value will indicate that a zero-inflated model is preferred.

[INSERT TABLE 4]

Spatial effects

Once we had defined the econometric methodology, neighboring effects also needed to be accounted for. The results may be biased and inconsistent if the location determinant effects of firm location decisions do not come only from the geographical limits of the area (i.e. neighborhood). To account for this spatial dependence, we used the Moran Index (Moran, 1948) and the Local Indicator of Spatial Association (Anselin, 1995) to test if there is some spatial dependence across variables. For this reason, we propose 2 spatial models to explain the effect of spatial dependence on firm location determinants: the Spatially Lagged Covariates Model (SLX) and the Spatial Autoregressive Poisson Model (P-SAR).[11] While the SLX model considers the spatially lagged variables of the independent variables, the P-SAR model considers the spatial autoregressive lag of the dependent variable. The first, the SLX model, is estimated as follows:

$$WX = W * X$$

where W is a row-standardized spatial neighbor matrix and X is a set of independent variables. The spatial neighbor matrix used follows the Queen Contiguity 1st order (i.e. it only takes into account the nearest 1st order neighbors). The spatial lagged variables were selected using the tests mentioned above.[12]

The P-SAR Model is a technique by Lambert et al. (2010) which formulates a two-step estimator for a spatial autoregressive lag model of counts. This technique can include the spatially lagged dependent variable in the model to explain if the dependent variable has any spatial dependence effect.

The first step (SAR estimation) involves replacing the spatially lagged, log-transformed counts in the y_i with their predicted values. Following Lambert et al. (2010), let the function $g(y_i)$ represent the logged-transformed values approximating neighboring

[11] The use of spatial count data models in firm location is innovative since these models are commonly used in other fields such as Ecology, Biostatistics or Medicine (Glaser, 2017). They are an improvement, because they explain what effect the surrounding areas have on the present area.

[12] See variable selection according Moran Index, aspatial significance of the variable and correlation between X and WX (table A4.) and the Local Indicator of Spatial Association of selected variables (figure A5.) in the annex.

counts. As it is useful to formulate the problem with reference to a log-likelihood function, the log-likelihood function of the first-stage estimator is:

$$lnL_1 = \sum_{i=1}^{n} f_1(W \cdot g(y_i)|Q_i; \delta)$$

where $f_1$is the normal probability density function and δ a vector of parameters that maximizes L_1. So, given a set of appropriately defined instrumental variables ($Q = [X, WX, WWX]$), the instruments regressed on the transformation yield the vector of predicted values:

$$Q\delta \text{ with } \delta = Q(Q'Q)^{-1}Q'W \cdot g\left(y_j^*\right)$$

Then, in the second step, the first-stage predicted values enter the Poisson probability density function as:

$$f(y|x, W, Q_i\delta'; \beta, \rho) = \frac{\exp(\beta' x_i + \rho \cdot Q_i'\delta)^{y_i} \exp(-\exp(\beta' x_i + \rho \cdot Q_i'\delta))}{y_i!}$$

This is essentially a Poisson regression with an endogenous covariate. We apply this procedure only to explain the spatial effect of the dependent variable of SVE firm entries, since it seems that this variable has some spatial dependence (see Figure 2).[13]

[INSERT FIGURE 2]

Unfortunately, the severe limitation of this technique is that it implies that all spatial dependency comes from observed covariates (Glaser, 2017). For this reason, we apply SLX to SVE, Creative and All firm entries and the P-SAR model only for SVE firm entries, since it is the only model which fits SVE firm entries and is the industry of interest in this paper. The use of both models enables us to see the spatial effect of the dependent variable as well as the effect of the covariates on SVE firm entries.

[13] Our estimation follows a two-step LIML estimation. We solve the problem of zero counts by transforming the dependent variable with the inverse hyperbolic sine transformation (Burbidge et al., 1988). For more information about the technique and procedures, see Lambert et al. (2010).

4. RESULTS

In this section, we present the results of our estimations. Table 5 gives our aspatial analysis (i.e. non-spatial approach) and Table 6 gives our spatial analysis (i.e. spatial approach).

Aspatial analysis

Table 5 presents the main results without spatial effects.[14] In order to avoid multicollinearity problems, a combination of agglomeration variables has been made (first only with the stock of firms of the same type [i.e. stock of SVE, Creative and All firms] and second, only using the sum stock of VFI, ADV and RTV of firms [i.e. *Aggl10* variable]).

[INSERT TABLE 5]

For agglomeration economies, the previous presence of SVE firms and the combination of VFI, ADV and RTV firms in the neighborhood positively affects the present location of SVE firms, as was shown by Méndez-Ortega and Arauzo-Carod (2019). For Creative and All firm models we also found that the previous presence of this type of firm had a positive effect. These are expected results and consistent with previous empirical research.

High-tech amenities have a positive and statistically significant impact on SVE firm entries and this effect is lower for Creative and All firm entries. This proves the importance of these amenities for the industry (Li and Zhu, 2017; Woodward et al., 2006). It is important to highlight the positive and significant effect of the 22@ district for SVE firm entries, as Viladecans-Marsal and Arauzo-Carod (2012) have proved. Cultural and creative diversity also have an impact on SVE firm entries. The positive and significant coefficients associated with the Entropy index and markets show that places with a high diversity of creative firms, street markets and diversity are places where SVE firms choose to locate, as empirical evidence has suggested (Florida and Gates, 2003; Florida and Mellander, 2016). The positive impact of these variables is slightly lower than that of creative firm entries but higher than that of All firm entries.

[14] We include Creative and all firm entry models so that we can compare the effect of some variables across type of entry, and thus have a more complete and rigorous analysis (Hypothesis 1).

Human capital variables are also important for high-tech firm entry decisions. We found that the presence of universities positively affects SVE firm entry decisions, while a high proportion of highly educated people and population density impacts positively on firm entry decisions for all models. These results are consistent with previous literature (Kinne and Resch, 2017). Finally, Crime negatively affects SVE and Creative firm location decisions, and is not significant for All entries. This shows that this type of firm tends to choose safe locations where there is no crime. These results contrast with those found by Goetz and Rupasingha (2002) and Hackler (2003), which showed a positive relationship between crime and entry growth rate of software firms.

In summary, these results confirm hypothesis 1, showing a positive effect of Agglomeration economies, High-tech amenities, Creative and Cultural Diversity and Human capital variables on SVE firm entry decisions and a negative effect of Crime. These effects are different across types of firm. Nevertheless, to test the second hypothesis – that is, whether the impact of certain variables transcends neighborhood borders – a spatial analysis needs to be done.

Spatial analysis (SAR-Poisson and Spatial Lag)

Table 6 presents the main results with spatial effects. The first column gives the results of the P-SAR model for SVE firm entries and the remaining five columns give the results of the SLX model for SVE, including spatial agglomeration variables (2), the spatial high-tech amenities variable (3), the spatial Creative and cultural diversity variable (4), the spatial Human capital variable (5) and the spatial Crime variable (6).

[INSERT TABLE 6]

For the P-SAR model, most of the key location determinant variables remain significant as in the previous estimation. The autoregressive coefficient (ρ) is statistically significant, which suggests that SVE firm neighboring entries are important and explain SVE firm entries.[15] This effect is explained by agglomeration economies, caused by the knowledge spillovers between firms, as literature and empirical evidence has proved. This determinant is much more intense in SVE firms, in which innovation and success is very closely tied to the talents of workers (Andersson et al., 2009). The impact of high-tech

[15] In this first estimation, the previous stock of SVE firms was not considered because of the high correlation with the autoregressive component.

amenities remains positive and significant (except for technology parks) as does the effect of craft street markets.

For the SLX models (2-6), almost all the key location determinants considered in the aspatial model remain positive and significant. In the case of lagged variables (*w_*), the presence of software firms around the neighborhood (*w_Sve10*) positively affects the location of SVE firms for all models except the first one. For the spatial lag of the High-tech variable, estimation (3) shows that there is a positive and significant effect on SVE entries in the neighborhoods surrounding the 22@ district, because of the importance of this high-tech district in attracting knowledge activity (Viladecans-Marsal and Arauzo-Carod, 2012).

Moreover, in the case of the Entropy index variable, the effect of including the spatial lag variable is negatively significant in (4) but not significant in (5-6), so diversity beyond borders does not affect SVE firm entry decisions. The spatial lag of crime is negatively significant, which shows that the presence of crime in surrounding neighborhoods also negatively affects SVE firm entries. Finally, the spatial lag of universities is not statistically significant in our SLX model.

Therefore, we almost confirmed Hypothesis 2 because, on the one hand, Agglomeration Economies and High-tech amenities have a positive impact and Crime a negative impact on SVE firm entries but, on the other hand, we found that the effect is not significant for all the variables beyond the borders (Entropy and University variables).

In summary, these results show that *i*) agglomeration economies, high-tech amenities and cultural and creative diversity are important factors in SVE firms' decisions to locate in a particular place within the city, and that these factors are different from those that affect the decisions of Creative and All firm entries. *ii)* In terms of spatial effects, the SLX model shows that there is a spatial effect beyond neighborhood borders for SVE firm entries, since almost all the lagged variables (*w_*) in SVE firm entry models were significant (except *w_Entropy* and *w_Universities*). Nevertheless, the P-SAR model shows a spatial effect in the dependent variable (*SVE firm entries*), which indicates that there is a positive spatial autoregressive effect (SVE firm entries are affected by surrounding SVE entries in the same period).

Robustness checks

We carried out a series of tests on the robustness of our results. First, we analyzed whether location patterns and effects of location determinants are the same for different firm sizes. The results were similar. Second, we tried to include variables such as distance from Plaça Catalunya (the cultural center of Barcelona), the number of coworking spaces and the number of civic centers (e.g. places where people who live in the neighborhood can do recreational activities, normally located in deprived areas), but these variables were not significant. Third, we used different criteria to select the spatial lagged variables (table A4.), but we tried to include the rest of variables and we obtain non-significant results for these variables. Fourth, we used different spatial neighbor matrices (5 k-nearest neighbors' matrix and Rook contiguity matrix) to test if the spatial effect varies. We observed that in the case of the P-SAR model, the more neighbors the matrix contains, the more diluted the effect of the autoregressive coefficient is (see table A6. in the annex). In the case of the SLX models, the results were similar, with the best choice being the 1st order Queen Contiguity matrix.

5. CONCLUSIONS

This paper has analyzed the main location determinants of software and video games firms in the city of Barcelona. In recent decades, this industry has changed the way in which people, firms and societies interact. Its impact on the current world economy is constantly growing, which makes it one of the most important industries in the world. Despite being an industry that is located mainly in cities, most empirical research on the location determinants of high-tech firms has been done at regional or country level.

So this paper has contributed to the literature by providing empirical evidence on the location determinants of this industry at urban level, and dealing with factors that have not been taken into account, or have not been analyzed together on this scale. Our main results show that SVE firms tend to choose locations with good high-tech amenities, a high diversity of creative firms and a presence of SVE and similar firms (i.e. agglomeration economies). Our hypothesis was confirmed since we found a positive effect of Agglomeration economies, High-tech amenities, Creative and Cultural Diversity and Human capital variables on SVE firm entry decisions and a negative effect of Crime. The methodological approach used in this paper provides a more in-depth understanding of the location strategies of these firms and supplements previous contributions with a methodology that has rarely been used in empirical studies because of its complexity.

These results raise some interesting issues for policy makers. To date, it has largely been assumed that SVE firms are located in places with technological facilities, human capital and good infrastructures in general. This paper has shown that these characteristics are indeed important, but so is cultural and creative diversity. These considerations can be extended to other cities from both developing and developed countries. Hence, the promotion and attraction of creative activities, in conjunction with the factors mentioned above, will contribute to the location of SVE activities, which are of fundamental importance to economic growth and will boost the economic development of cities.

Nevertheless, this paper has some limitations that we intend to address in further research. Although the unit of analysis is small (i.e. neighborhood), it must be taken into account that there is a modifiable areal unit problem (MAUP). Moreover, the paper deals with a specific city and period of time. Further research should explore all these concerns in other to provide more robust results.

Acknowledgements:

This article has benefited from funding from FEDER/Ministerio de Ciencia, Innovación y Universidades (project ECO2017-88888-P), the "Xarxa de Referència d'R+D+I en Economia i Polítiques Públiques" and the research programme SGR (2017-SGR-159). I am grateful for the support provided by J.M. Arauzo-Carod, E. Coll-Martínez and K. Miranda and for the comments received at REAL Fall 2018 Seminar, 65th North American Regional Science Conference, 7th PhD-Student WIPE, ECONRES Seminar, AQR Seminar and 2nd Catalan Economic Society Conference. Any errors are, of course, my own.

REFERENCES:

Abel, J. R., & Deitz, R. (2012). Do colleges and universities increase their region's human capital? *Journal of Economic Geography*, *12*(3), 667–691. https://doi.org/10.1093/jeg/lbr020

Abramovsky, L., & Simpson, H. (2011). Geographic proximity and firm-university innovation linkages: Evidence from Great Britain. *Journal of Economic Geography*, *11*(6), 949–977. https://doi.org/10.1093/jeg/lbq052

Acosta, M., Coronado, D., & Flores, E. (2011). University spillovers and new business location in high-technology sectors: Spanish evidence. *Small Business Economics*, *36*(3), 365–376. https://doi.org/10.1007/s11187-009-9224-4

Andersson, F., Freedman, M., Haltiwanger, J., Lane, J., & Shaw, K. (2009). Reaching for the stars: Who pays for talent in innovative industries? *Economic Journal*, *119*(538), 308–332. https://doi.org/10.1111/j.1468-0297.2009.02277.x

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Arauzo-Carod, J.-M., Liviano-Solis, D., & Manjón-Antolín, M. (2010). Empirical Studies in Industrial Location: an Assessment of Their Methods and Results. *Journal of Regional Science*, *50*(3), 685–711. https://doi.org/10.1111/j.1467-9787.2009.00625.x

Arauzo-Carod, J.-M., Liviano, D., & Manjón-Antolín, M. C. (2010). Empirical Studies in Industrial Location: an Assessment of Their Methods and Results. *Journal of Regional Science*, *50*(3), 685–711. https://doi.org/10.1111/j.1467-9787.2009.00625.x

Arauzo-Carod, J.-M., & Viladecans-Marsal, E. (2009). Industrial Location at the Intra-Metropolitan Level: The Role of Agglomeration Economies. *Regional Studies*, *43*(4), 545–558. https://doi.org/10.1080/00343400701874172

Audretsch, D. B., & Keilbach, M. (2004). Entrepreneurship capital and economic performance. *Regional Studies*, *38*(8), 949–959. https://doi.org/10.1080/0034340042000280956

Audretsch, D. B., & Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? *Research Policy*, *34*(8), 1191–1202. https://doi.org/10.1016/j.respol.2005.03.012

Berger, T., & Frey, C. B. (2016). Did the Computer Revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs. *Regional Science and Urban Economics*, *57*, 38–45. https://doi.org/10.1016/j.regsciurbeco.2015.11.003

Boix, R., & Lazzeretti, L. (2012). Las industrias creativas en España: Una panorámica. *Investigaciones Regionales*, (22), 181–205.

Brülhart, M., Jametti, M., & Schmidheiny, K. (2012). Do agglomeration economies reduce the sensitivity of firm location to tax differentials? *Economic Journal*, *122*(563), 1069–1093. https://doi.org/10.1111/j.1468-0297.2012.02511.x

BSA, & The Economist Intelligence Unit. (2016). *Software: A €910 Billion Catalyst for the EU Economy*. Retrieved from www.bsa.org/EUSoftwareImpact

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformation to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83*(401), 23–127. https://doi.org/10.2307/2288929

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (Vol. 53). Cambridge university press.

Chatman, D. G., & Noland, R. B. (2011). Do Public Transport Improvements Increase Agglomeration Economies? A Review of Literature and an Agenda for Research. *Transport Reviews*, *31*(6), 725–742.

Coll-Martínez, E., Moreno-Monroy, A. I., & Arauzo-Carod, J.-M. (2019). Agglomeration of creative industries: An intra-metropolitan analysis for Barcelona. *Papers in Regional Science*, *98*(1), 409–431. https://doi.org/10.1111/pirs.12330

De Propris, L. (2013). How are creative industries weathering the crisis? *Cambridge Journal of Regions, Economy and Society*, *6*(1), 23–35. https://doi.org/10.1093/cjres/rss025

Duranton, G., & Puga, D. (2004). Micro-Foundations of Urban Agglomeration Economies. In *Handbook of Regional and Urban Economics Vol.4* (pp. 2063–2111).

Duvivier, C., & Polèse, M. (2017). The great urban techno shift: Are central neighbourhoods the next silicon valleys? Evidence from three Canadian metropolitan areas. *Papers in Regional Science*. https://doi.org/10.1111/pirs.12284

Fernhaber, S. A., Gilbert, B. A., & McDougall, P. P. (2008). International entrepreneurship and geographic location: An empirical examination of new venture internationalization. *Journal of International Business Studies*, *39*(2), 267–290. https://doi.org/10.1057/palgrave.jibs.8400342

Figueiredo, O., Guimarães, P., & Woodward, D. (2002). Home-field advantage: Location decisions of Portuguese entrepreneurs. *Journal of Urban Economics*, *52*(2), 341–361. https://doi.org/10.1016/S0094-1190(02)00006-2

Florida, R., & Gates, G. (2003). TECHNOLOGY AND TOLERANCE: THE IMPORTANCE OF DIVERSITY TO HIGH-TECHNOLOGY GROWTH. In T. N. Clark (Ed.), *The City as an Entertainment Machine* (p. 325). https://doi.org/10.1016/S1479-3520(03)09001-9

Florida, R., & Mellander, C. (2009). There goes the metro: How and why bohemians, artists and gays affect regional housing values. *Journal of Economic Geography*, *10*(2), 167–188. https://doi.org/10.1093/jeg/lbp022

Florida, R., & Mellander, C. (2016). Rise of the startup city: The changing geography of the venture capital financed innovation. *California Management Review*, *59*(1), 14–38. https://doi.org/10.1177/0008125616683952

Frenkel, A. (2012). Intra-metropolitan Competition for Attracting High-technology Firms. *Regional Studies*, *46*(6), 723–740. https://doi.org/10.1080/00343404.2010.529120

Giblin, M. (2011). Managing the global-local dimensions of clusters and the role of “lead” organizations: The contrasting cases of the software and medical technology clusters in the west of Ireland. *European Planning Studies*, *19*(1), 23–42. https://doi.org/10.1080/09654313.2011.530529

Gilbert, B. A. (2017). Agglomeration, Industrial Districts and Industry Clusters: Trends of the 21st Century Literature. *Foundations and Trends® in Entrepreneurship*, *13*(1), 1–80. https://doi.org/10.1561/0300000069

Glaser, S. (2017). *A review of spatial econometric models for count data* (Hohenheim Discussion Papers in Business, Economics and Social Sciences No. 19). Hohenheim. Retrieved from http://economicsandpeace.org/

Goetz, S. J., & Rupasingha, A. (2002). High-Tech Firm Clustering: Implications for Rural Areas. *American Journal of Agricultural Economics*, *84*(5), 1229–1236. https://doi.org/10.1111/j.1540-6296.2010.01192.x

Gómez-Antonio, M., & Sweeney, S. (2018). Firm location, interaction, and local characteristics:

A case study for Madrid's electronics sector. *Papers in Regional Science*, *97*(3), 663–685. https://doi.org/10.1111/pirs.12274

Hackler, D. (2003). High-tech location in five metropolitan areas. *Journal of Urban Affairs*, *25*(5), 625–640. https://doi.org/10.1111/j.1467-9906.2003.00005.x

Howkins, J. (2001). *The Creative Economy: How People Make Money from Ideas*. Penguin UK.

INE. (2016). Information and Communications Technologies (ICT) Sector Indicators. Retrieved May 22, 2019, from http://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736176742&menu=resultados&idp=1254735576692

Jacobs, J. (1969). *The Economies of cities*. New York: Random House.

Kim, Y. L. (2018). Seoul's Wi-Fi hotspots: Wi-Fi access points as an indicator of urban vitality. *Computers, Environment and Urban Systems*, 1–12. https://doi.org/10.1016/j.compenvurbsys.2018.06.004

Kinne, J., & Resch, B. (2017). Analyzing and Predicting Micro-Location Patterns of Software Firms. *ISPRS International Journal of Geo-Information*, *7*(1), 1. https://doi.org/10.3390/ijgi7010001

Lambert, D. M., Brown, J. P., & Florax, R. J. G. M. (2010). A two-step estimator for a spatial lag model of counts: Theory, small sample performance and an application. *Regional Science and Urban Economics*, *40*(4), 241–252. https://doi.org/10.1016/j.regsciurbeco.2010.04.001

Li, M., Goetz, S. J., Partridge, M., & Fleming, D. A. (2016). Location determinants of high-growth firms. *Entrepreneurship and Regional Development*, *28*(1–2), 97–125. https://doi.org/10.1080/08985626.2015.1109003

Li, Y., & Zhu, K. (2017). Spatial dependence and heterogeneity in the location processes of new high-tech firms in Nanjing, China. *Papers in Regional Science*, *96*(3), 519–535. https://doi.org/10.1111/pirs.12202

Liviano, D., & Arauzo-Carod, J.-M. (2012). Industrial Location and Spatial Dependence: An Empirical Application. *Regional Studies*, *3404*(July 2014), 1–17. https://doi.org/10.1080/00343404.2012.675054

Lucas, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, *22*(February), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Lyons, D. (1995). Agglomeration Economies among High Technology Firms in Advanced Production Areas: The Case of Denver/Boulder. *Regional Studies*, *29*(3), 265–278. https://doi.org/10.1080/00343409512331348953

Marra, A., Cassetta, E., & Antonelli, P. (2017). Emerging specialisations and software metropolitan clusters - a comparative network analysis on San Francisco, New York and London. *International Journal of Technological Learning, Innovation and Development*, *9*(1), 17. https://doi.org/10.1504/IJTLID.2017.10003733

Marshall, A. (1890). *Principles of Economics*. Macmillan: London.

Méndez-Ortega, C., & Arauzo-Carod, J.-M. (2019). Do Software and Videogames firms share location patterns across cities? Evidence from Barcelona, Lyon and Hamburg. *The Annals of Regional Science*, Forthcoming.

Moran, P. A. P. (1948). The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society. Series B*, *10*(2), 243–251.

Rosenthal, S. S., & Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2119–2171). Elsevier Inc. https://doi.org/10.1016/S1574-0080(04)80006-3

Theil, H. (1974). *Statistical Decomposition Analysis* (North-Holl). Amsterdam: North-Holland.

UNCTAD. (2010). *Creative economy Report*. Geneva. Retrieved from https://unctad.org/en/docs/ditctab20103_en.pdf

Viladecans-Marsal, E., & Arauzo-Carod, J.-M. (2012). Can a knowledge-based cluster be created? The case of the Barcelona 22at district. *Papers in Regional Science*, *91*(2), 377–400. https://doi.org/10.1111/j.1435-5957.2011.00383.x

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, *57*(2), 307–333.

Wang, K.-J., Lestari, Y. D., & Tran, V. N. B. (2017). Location Selection of High-tech Manufacturing Firms by a Fuzzy Analytic Network Process: A Case Study of Taiwan High-tech Industry. *International Journal of Fuzzy Systems*, *19*(5), 1560–1584. https://doi.org/10.1007/s40815-016-0264-z

Wood, S., & Dovey, K. (2015). Creative Multiplicities: Urban Morphologies of Creative Clustering. *Journal of Urban Design*. Taylor & Francis. https://doi.org/10.1080/13574809.2014.972346

Woodward, D., Figueiredo, O., & Guimarães, P. (2006). Beyond the Silicon Valley: University R&D and high-technology location. *Journal of Urban Economics*, *60*(1), 15–32. https://doi.org/10.1016/j.jue.2006.01.002

Yamamura, S., & Goto, H. (2018). Location patterns and determinants of knowledge- intensive industries in the Tokyo Metropolitan Area. *Japan Architectural Review*, 1–14. https://doi.org/10.1002/2475-8876.12039

Zandiatashbar, A., & Hamidi, S. (2018). Impacts of transit and walking amenities on robust local knowledge economy. *Cities*. https://doi.org/10.1016/j.cities.2018.04.005

TABLES

Table 1. Summary of recent location studies on high-tech, knowledge-based and/or SVE firms

Studies	*LAE*	*HTA*	*CCD*	*HC*	*LPT*	*C*
Abramovsky and Simpson (2011)	X	X		X		
Acosta et al. (2011)	X	X		X	X	
Audretsch and Lehmann (2005)	X	X		X		
Audretsch and Keilbach (2004)		X		X		
Chatman and Noland (2011)	X	X		X		
Marra et al. (2017)	X					
Florida and Mellander (2016)	X	X	X	X		
Florida and Mellander (2009)				X	X	
Goetz and Rupasingha (2002)	X			X	X	X
Hackler (2003)	X	X		X		X
Kinne and Resch (2017)	X	X		X	X	X
Li and Zhu (2017)	X	X		X		
Li et al. (2016)	X			X	X	
Méndez-Ortega and Arauzo-Carod (2019)	X	X	X			
Viladecans-Marsal and Arauzo-Carod (2012)	X	X		X		
Wang et al. (2017)	X	X			X	
Wood and Dovey (2015)	X		X	X	X	
Woodward et al. (2006)	X	X		X	X	
Zandiatashbar and Hamidi (2018)	X	X	X	X		

Source: Author. Note: *LAE* (Localization and Agglomeration Economies), *HTA* (High-Tech Amenities), *CCD* (Cultural and Creative Diversity), *HC* (Human Capital), *LPT* (Land Price and Tax) and *C* (Crime).

Table 2. Descriptive statistics of covariates by neighborhood

Acronym	Description	Expected effect	Source	Mean	Standard Deviation	Max	Min
Agglomeration economies							
Loc10(SVE)	Stock of SVE firms in 2010	+	SABI	23.232	44.587	283	0
Loc10(Cre)	Stock of Creative firms in 2010	+	SABI	106.689	187.007	1075	0
Loc10 (all)	Stock of all firms in 2010	+	SABI	866.698	1599.765	9552	8
Aggl10	Stock of VFI, ADV and RTV firms in 2010	+	SABI	31.041	64.203	378	0
	High-tech Amenities						
Wifi	Nº of Wi-Fi Hotspots in the neighborhood	+	OD-BCN	8.096	10.443	56	0
CTP	Nº of Scientific and Technology parks	?	A	0.110	0.315	1	0
Dist22	Dummy var. (value 1 whether the neighborhood belongs to 22@)	+	A	0.0548	0.229	1	0
	Diversity						
Entropy*	Entropy index of Creative firms in 2010	+	A	0.675	0.202	0.880	0
Markets	Nº of Craft street Markets in 2010	?	OD-BCN	1.342	1.988	12	0
	Human Capital						
University	Nº of universities (faculties) in 2010	+	A	0.808	1.838	11	0
Edu10	Proportion of high educated population in 2010	+	OD-BCN	0.213	0.121	0.497	0.022
Popd10	Population density (pop. per residential surface) in 2010	+	OD-BCN	692.962	305.875	1504	30.054
	Crime						
PolRat	Nº of police incidents per 1000 hab	-	OD-BCN	2.334	2.488	14.90	0.0650

Note: A (Author), OD-BCN (Open Data Barcelona). (*) This index is an indicator of equality (Theil, 1974) which ranges between 0 and 1 to detect whether a spatial unit is homogeneous or diverse. In our case we apply this index to the diversity of creative firms in the area (i.e. neighborhood).

Table 3. Descriptive statistics of dependent variables

Acronym	Description	Mean	Standard deviation	Max	Min	% of Zeros
Sve_ent	SVE firm entries 2011-2013	4.479	8.386	44	0	32.87
Cre_ent	Creative firm entries 2011-2013	16.082	29.254	167	0	19.17
All_ent	All firm entries 2011-2013	92.671	175.980	1127	0	2.73

Source: Author.

Table 4. Selection model's tests

	AIC	BIC	Vuong Test
Model 1 (SVE firms)			
Poisson	286.349	320.706	-
Negative binomial	302.665	334.732	-
Zero-inflated Poisson	290.021	328.959	0.526
Zero-inflated negative binomial	304.513	341.161	0.205
Model 2 (Creative firms)			
Poisson	415.352	447.136	-
Negative binomial	392.779	427.136	-
Zero-inflated Poisson	414.131	450.778	0.731
Zero-inflated negative binomial	396.779	435.717	-0.149
Model 3 (All firms)			
Poisson	1188.898	1220.964	-
Negative binomial	663.867	698.224	-
Zero-inflated Poisson	1172.139	1208.7871	1.296
Zero-inflated negative binomial	656.856	695.794	1.183

Source: Author.

Table 5. Location determinants of firms (Aspatial)

	Software and video game firms		Creative firms	All firms
	PM		NBM	NBM
	(1)	(2)	(3)	(4)
***Agglomeration* Economies**				
Loc10	0.00783***		0.00193***	0.000298***
	(0.00137)		(0.000361)	(6.11e-05)
Aggl10		0.00638***		
		(0.00109)		
High-Tech Amenities				
Wifi	0.0206**	0.0249***	0.0138**	0.0229**
	(0.00824)	(0.00780)	(0.00699)	(0.0104)
CTP	0.378*	0.474**	0.162	0.932***
	(0.221)	(0.222)	(0.215)	(0.265)
Dist22	0.956***	0.902***	0.410*	-0.189
	(0.239)	(0.237)	(0.232)	(0.298)
Cultural and Creative Diversity				
Entropy	3.321***	3.359***	7.217***	2.635***
	(1.266)	(1.238)	(1.245)	(0.500)
Markets	0.101***	0.125***	0.0691***	0.0788**
	(0.0300)	(0.0323)	(0.0258)	(0.0386)
Human Capital				
University	0.0615**	0.0695***	0.0353	-0.0218
	(0.0271)	(0.0267)	(0.0286)	(0.0416)
Edu10	5.254***	4.361***	5.433***	2.718***
	(1.048)	(1.090)	(0.854)	(0.742)
Popd10	0.000941***	0.000982***	0.000749***	0.000544*
	(0.000323)	(0.000322)	(0.000269)	(0.000278)
Crime				
PolRat	-0.107**	-0.134***	-0.0537	0.00390
	(0.0435)	(0.0446)	(0.0330)	(0.0447)
Constant	-3.897***	-3.761***	-5.894***	0.154
	(0.865)	(0.842)	(0.915)	(0.335)
Observations	73	73	73	73
Non-zero observations	49	49	59	71
LR chi2	569.7	571.8	152.5	151.5
Log likelihood	-137.5	-136.4	-160.2	-310.1
Pseudo R-squared	0.674	0.677	0.323	0.196
/ln alpha			-3.124***	-1.501***
			(0.676)	(0.207)
alpha			0.0454	0.227
VIF	2.26	2.23	2.25	2.21

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Loc10 refers to stock of the current type of firms in 2010. Poisson Model (PM), Negative Binomial Model (NBM).

Table 6. Location determinants of firms (P-SAR and SLX models)

	Software and video game firms					
	P-SAR			SLX		
	(1)	(2)	(3)	(4)	(5)	(6)
Agglomeration Economies						
Sve10		0.00763***	0.00843***	0.00853***	0.0115***	0.0114***
		(0.00137)	(0.00144)	(0.00144)	(0.00159)	(0.00161)
High-Tech Amenities						
Wifi	0.0411***	0.0218***	0.0203**	0.0225***	0.0186**	0.0206**
	(0.00764)	(0.00830)	(0.00836)	(0.00847)	(0.00876)	(0.00903)
CTP	0.199	0.531**	0.636***	0.809***	1.361***	1.425***
	(0.239)	(0.240)	(0.245)	(0.269)	(0.311)	(0.315)
Dist22	1.041***	0.966***	0.632**	0.579**	0.0126**	0.00298*
	(0.240)	(0.240)	(0.288)	(0.290)	(0.320)	(0.321)
Cultural and Creative Diversity						
Entropy	1.843	2.933**	3.146**	4.136***	4.088***	3.917***
	(1.193)	(1.235)	(1.258)	(1.384)	(1.383)	(1.372)
Markets	0.0620*	0.0919***	0.0965***	0.0991***	0.0563*	0.0762**
	(0.0323)	(0.0308)	(0.0311)	(0.0313)	(0.0320)	(0.0368)
Human Capital						
University	0.0932***	0.0356*	0.0341*	0.0201*	0.0289*	0.0367*
	(0.0274)	(0.0316)	(0.0316)	(0.0329)	(0.0385)	(0.0396)
Edu10	5.574***	4.574***	3.900***	4.469***	2.629*	2.989**
	(1.554)	(1.127)	(1.158)	(1.232)	(1.412)	(1.449)
Popd10	0.000559	0.000758**	0.000665*	0.000779**	0.000854**	0.000844*
	(0.000396)	(0.000345)	(0.000347)	(0.000361)	(0.000390)	(0.000394)
Crime						
PolRat	-0.0532	-0.112***	-0.114***	-0.115***	-0.00295*	-0.0224*
	(0.0375)	(0.0432)	(0.0429)	(0.0428)	(0.0527)	(0.0553)
Spatial Variables						
ρ	0.0866**					
	(0.0351)					
w_Sve10		0.00382	0.00460*	0.00585**	0.0157***	0.0158***
		(0.00240)	(0.00243)	(0.00253)	(0.00342)	(0.00343)
w_Dist22			0.874**	1.023**	1.344***	1.239***
			(0.412)	(0.424)	(0.412)	(0.421)
w_Entropy				-2.636*	-0.433	-0.287
				(1.566)	(1.718)	(1.714)
w_PolRat					-0.398***	-0.391***
					(0.0908)	(0.0910)
w_University						-0.0989
						(0.0875)
θ	0.338**					
	(0.156)					
Constant	-3.095***	-3.418***	-3.444***	-2.565***	-3.248***	-3.228***
	(0.852)	(0.866)	(0.874)	(0.949)	(1.061)	(1.049)
Observations	73	73	73	73	73	73
Non-zero observations	49	49	49	49	49	49

LR chi2	537	572.2	576.2	578.8	600.6	601.9
Log likelihood	-153.8	-136.2	-134.2	-132.9	-122	-121.4
Pseudo R-squared	0.636	0.677	0.682	0.685	0.711	0.713

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Poisson Spatial Autoregressive Model (P-SAR), Spatial Lag Model (SLX).

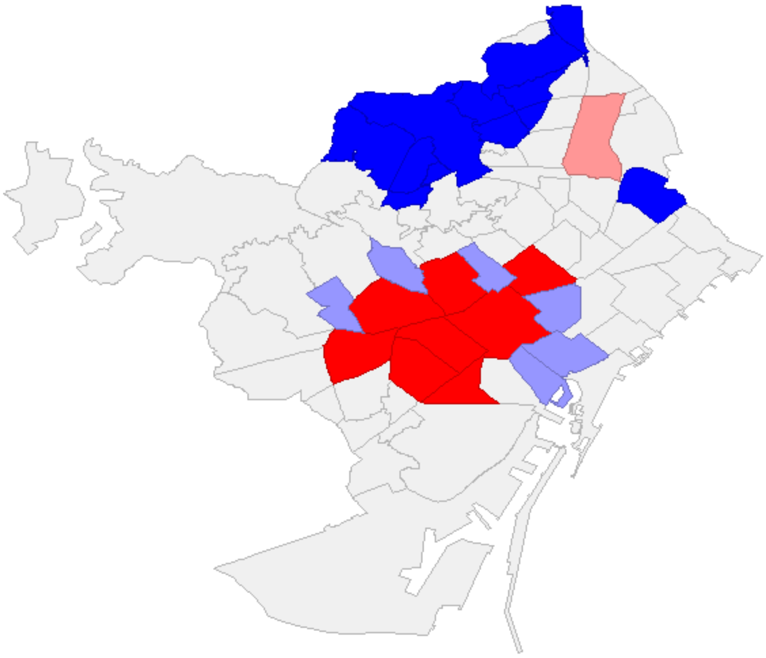
FIGURES

Figure 1. City of Barcelona by neighborhoods (73)

Source: Barcelona Statistics Service (www.bcn.cat/estadistica).

Figure 2. Local indicator of spatial association (LISA) and Moran Index for SVE firm entries

***SVE_ent* (0.373)**



Source: Author. Note: Moran index in brackets. Red indicates neighborhoods with a high value surrounded by neighborhoods with a high value, light red means neighborhoods with a high value surrounded by neighborhood with a low value, light blue means neighborhoods with a low value surrounded by neighborhoods with a high value and blue means neighborhoods with a low value surrounded by neighborhoods with low value. Results after 999 permutations.

ANNEX

Table A1. List of creative industries

Nº	**Creative industries**	**Acronym**	**NACE 2009 Codes**
1	Advertising and related services	ADV	731
2	Architecture and engineering	AE	711
3	Art and antiques trade	ART	4779
4	Craft and performing arts	CPA	90
5	Cultural tourism and recreational services	TRS	93
6	Publishing	ED	581
7	Fashion	FA	14, 1511, 152
8	Graphic arts	GA	181
9	Heritage, cultural sites and recreational services	HE	91
10	Creative research and development	IDC	721, 722
11	Jewellery, musical instruments, toys and games	JEW	321, 322, 324
12	Music and music studies	MU	182, 592
13	Photography	PHO	742
14	Radio and TV	RTV	601, 602
15	Software, video games and editing electronics	SVE	620, 582
16	Specialised services design	SSD	741
17	Video and film industries	VFI	591

Source: Own elaboration based on UNCTAD (2010)

Table A2. Determinants of rent price in Barcelona by neighborhood (2011)

	Rent Price			
	SVE firms		Creative firms	All firms
	(1)	(2)	(3)	(4)
Loc10	-0.00980**		-0.00231*	-0.000226*
	(0.00467)		(0.00116)	(0.000129)
Aggl10		-0.00643*		
		(0.00352)		
Wifi	-0.00140	-0.00955	-0.00796	-0.00920
	(0.0237)	(0.0225)	(0.0223)	(0.0230)
CTP	0.509	0.452	0.467	0.479
	(0.512)	(0.517)	(0.514)	(0.517)
Dist22	0.137	0.160	0.179	0.0224
	(0.583)	(0.587)	(0.585)	(0.592)
Entropy	-0.0329	-0.0637	-0.0564	0.0338
	(0.895)	(0.905)	(0.899)	(0.902)
Markets	0.0386	0.0238	0.0293	0.0445
	(0.0801)	(0.0816)	(0.0808)	(0.0809)
University	0.00641	0.000828	0.00401	0.00450
	(0.0872)	(0.0878)	(0.0874)	(0.0883)
Edu10	15.45***	15.59***	15.80***	15.34***
	(1.644)	(1.680)	(1.692)	(1.659)
Popd10	0.00178***	0.00174***	0.00175***	0.00177***
	(0.000501)	(0.000509)	(0.000505)	(0.000509)
PolRat	0.0530	0.0797	0.0830	0.0621
	(0.0872)	(0.0883)	(0.0880)	(0.0879)
Constant	4.978***	4.990***	4.959***	4.980***
	(0.510)	(0.515)	(0.512)	(0.516)
Observations	73	73	73	73
R-squared	0.755	0.751	0.753	0.750

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Loc10 refers to stock of the current type of firms in 2010.

Table A3. Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	***Wifi***	1								
(2)	***CTP***	-0.096	1							
(3)	***Dist22***	0.096	0.108	1						
(4)	***Entropy***	0.412*	0.066	0.133	1					
(5)	***Markets***	0.346*	-0.083	-0.042	0.223	1				
(6)	***University***	0.162	0.517*	-0.008	0.206	0.052	1			
(7)	***Edu10***	0.475*	0.099	-0.065	0.583*	0.138	0.385*	1		
(8)	***Popd10***	0.073	-0.234*	0.211	0.208	0.114	-0.137	-0.252*	1	
(9)	***PolRat***	0.664*	0.081	-0.017	0.448*	0.607*	0.190	0.307	0.174	1

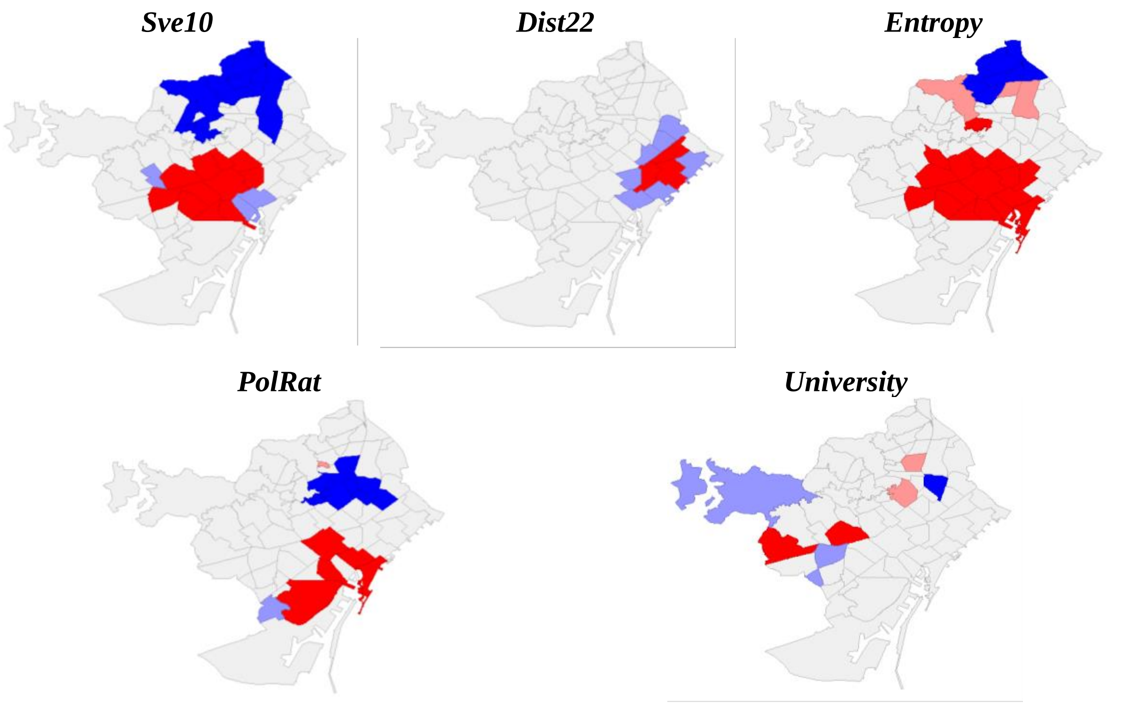
Source: Author. Note: (*) Significance level at 5%.

Table A4. Selection of Spatial Lag variables (SLX Model)

Variable	Correlation with WX	Moran I	Sig. Aspatial	SLX Model
Sve10	0.574*	0.406	Yes	Yes
Wifi	0.618*	0.447	Yes	No
CTP	0.134	0.060	Yes	No
Dist22	0.472*	0.343	Yes	Yes
Entropy	0.739*	0.566	Yes	Yes
Markets	0.089*	0.046	Yes	No
PolRat	0.668*	0.478	Yes	Yes
University	0.291*	0.143	Yes	Yes
Edu10	0.841*	0.681	Yes	No
Popd10	0.385*	0.240	Yes	No

Source: Author. Note: Sig. Aspatial indicates whether this variable was significant in the aspatial model.

Figure A5. Local indicator of spatial association (LISA) for selected SLX model variables.



Source: Author.

Table A6. Neighbor matrices test for the P-SAR model

W matrix	(1) 1st Order Queen Contiguity	(2) 5-k nearest neighbors	(3) 1st Order Rook Contiguity
ρ	0.0866**	0.0317*	0.0774**
	(0.0351)	(0.0176)	(0.0667)
Constant	-3.095***	-3.408***	-3.128***
	(0.852)	(0.838)	(0.859)
θ	0.338**	0.371**	0.335**
	(0.156)	(0.166)	(0.154)
AE var.	Yes	Yes	Yes
HTA var.	Yes	Yes	Yes
CCD var.	Yes	Yes	Yes
HC var.	Yes	Yes	Yes
Crime var.	Yes	Yes	Yes
Observations	73	73	73
Non-zero observations	49	49	49
LR chi2	537	535.6	536.6
Log likelihood	-153.8	-154.5	-154
Pseudo R-squared	0.636	0.634	0.635

Standard errors in parentheses. Notation: *** p<0.01, ** p<0.05, * p<0.1. Note: This table only shows main results; the rest of the results are available upon request.