INDUSTRY AND INNOVATION
2021, VOL. 28, NO. 10, 1225–1248
https://doi.org/10.1080/13662716.2021.1929868

Location determinants of high-tech firms: an intra-urban approach

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ABSTRACT

This paper analyses location determinants of high-tech firms at the intra-urban level, concretely for neighbourhoods of Barcelona. Mercantile Register data is used to analyse the location of 515 firms between 2011 and 2013 through count data estimations. The identification of the location patterns, followed by a typology of the firms, and the role played by neighbourhood characteristics in attracting them, constitutes a contribution to the empirical literature. Our results help in understanding the entry processes within cities and show that *i)* there are certain specificities at industry level, *ii)* that both amenities and economic-oriented neighbourhood characteristics matter, and *iii)* that spatial spillovers are relevant for some high-tech industries.

KEYWORDS

Location decisions; *count data*; *cities*; *intra-urban level*; *spatial econometrics*; *high-tech*

JEL

O30; *R10*; *R39*

1. Introduction

For many territories, new business constitutes one of their main sources of growth of economic activity and job creation (Arauzo-Carod, Liviano-Solís, and Manjón-Antolín 2010). Hence the location decisions taken by firms are of major importance to them. Following on from the seminal contributions of Marshall (1890), many scholars have analysed location decisions processes and the consequent spatial distribution of economic activity. Throughout most of the 20th century, contributions to location analysis have approached this phenomenon in wide-ranging ways, studying large geographical areas, but with limited information about the entering firms. More recently, the availability of richer datasets, and the implementation of more sophisticated econometric methodologies, have enabled out studies that provide new insights about the location determinants of entering firms.

This paper aims to contribute to the empirical location literature by attempting to shed light on four specific lesser-studied areas. First, most location analyses have used wide geographical areas as potential sites to be chosen by entering firms (Autant-Bernard, Mangematin, and Massard 2006). Second, they have analysed entering firms by grouping them without detailed consideration of how industry-specific characteristics may influence their location preferences (Liviano and Arauzo-Carod 2014). Third, they have neglected the influence of neighbouring areas (Andersson and Hellerstedt 2009) and, finally, they have not considered the effects of

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local non-economic characteristics on these location decisions (Artal-Tur et al. 2012). Our study aims at addressing these limitations by *i)* analysing firm location at intra-city level instead of considering cities as homogeneous areas, *ii)* disaggregating industries and focusing only on certain types of them, *iii)* taking into account the location dynamics and socioeconomic conditions of neighbouring areas, and *iv)* correctly estimating a detailed vector of local characteristics that may influence location decisions. Although it is true that some previous contributions have partially solved these limitations (especially for Chinese cities), this paper offers a unified approach to them all.

Specifically, this paper analyses the location determinants of a selection of high-tech industries[1] at the urban level for neighbourhoods of Barcelona, the capital of Catalonia, an autonomous region in northeast Spain[2] that has about 1.5 million inhabitants in an area of 101 km^2. We consider both economic and amenity-based characteristics among the local characteristics that may influence such location decisions. The former obviously influence location decisions since they concern specific inputs required by firms, whilst the latter ones relate to quality of life for skilled workers (a key concern for high-tech firms) and, therefore, increase a city's attractiveness.

The urban/intra-urban focus of this paper relies on several theoretical considerations which suggest that cities should provide: *i)* amenities that attract the most skilled individuals (Glaeser, Ponzetto, and Zou 2016), specifically those used intensively by high-tech industries; *ii)* a high availability of specialised suppliers and customers (Antonietti, Cainelli, and Lupi 2013); *iii)* reduced transport and transaction costs (Antonietti, Cainelli, and Lupi 2013); *iv)* networking opportunities (Arzaghi and Henderson 2008), and *v)* specialised and skilled labour (Combes, Duranton, and Gobillon 2008; Arai et al. 2004). As activities carried out by high-tech firms benefit from the agglomeration economies existing in large metropolitan areas (Arai et al. 2004), we hypothesise that, given that the spatial range of agglomeration economies is quite short,[3] these benefits are not homogeneously spread inside areas but are, on the contrary, concentrated in sub-centres (Smętkowski, Celińska-Janowicz, and Wojnar 2021), which explains why it is important to 'zoom in' on big cities and use smaller neighbourhoods as study units. Spatial proximity among similar firms is, therefore, an important source of competitiveness, especially for high-tech industries, as they require face-to-face interactions to exchange complex and tacit knowledge (Isaksen 2004). Our results show the specificities of the location patterns of high-tech industries, the relevance of policy measures in targeting their attraction, and the important role played by knowledge-based infrastructures and accessibility to human capital on new firms' location.

The structure of this paper is as follows: the second section reviews the location literature and addresses the main points raised by scholars, the third section details the characteristics of the dataset and provides some descriptive statistics, the fourth section describes the methodology (local spatial autocorrelation analysis and count data

[1]Concretely, Video & TV Production, Wired Telecommunications and Other Telecommunications, Computer Programming & Consultancy, and Data processing & Hosting, Other Information Services and R&D Natural Sciences & Engineering, and R&D Social Sciences & Humanities.

[2]The Catalan case has been widely analysed using different approaches. Liviano and Arauzo-Carod (2014, 2013) focused on the 'zero problem' (i.e., the existence of a threshold in terms of whether a site can be chosen by a firm) and the role of spatial effects on extreme overdispersion. Arauzo-Carod (2008) and Arauzo-Carod and Manjón-Antolín (2012) considered the spatial units to be used for location analyses.

[3]Coll-Martínez, Moreno-Monroy, and Arauzo-Carod (2019) analyse the spatial extent of agglomeration of creative industries in Barcelona (as a proxy of agglomeration economies) and conclude that it ranges between 0 and 1 km.

regression models) and discusses the main results, and the fifth section concludes and suggests the directions for further analyses.

2. Literature review

Location decisions of firms constitute an important topic in the Economics literature, attracting considerable attention from researchers as is shown in the review article by Arauzo-Carod, Liviano-Solís, and Manjón-Antolín (2010). Location decisions are very relevant as there are key implications in terms of competitiveness, market accessibility, and firms' performance and survival depending on the area chosen by an entering firm. Accordingly, firms try to select the best hotspots for their potential markets at the same time as benefitting from an innovative environment, enjoying good accessibility to a specialised workforce, operating in a prestigious area and taking advantage of a wide diversity of urban amenities (Frenkel 2001).

Empirical contributions about location decisions of firms have, in the main, approached this topic from two different perspectives: the point of view of the firm, and the point of view of the areas where these firms may locate. This distinction also implies different methodologies, the former analyses rely on discrete choice models, while the latter are mainly based on count data models. Given that we are interested in the spatial asymmetries that determine firms' decisions, we will focus mainly on the latter approaches.

In this area, the empirical literature has found that agglomeration economies matter for the location of new high-tech firms because these firms tend to benefit from efficiency gains arising from core and densely agglomerated areas (Woodward, Figueiredo, and Guimarães 2006).[4] From a theoretical approach, micro-foundations of agglomeration economies arise from benefits in terms of sharing, matching and learning when firms locate close to each other (Duranton and Puga 2004).

Sharing mechanisms imply that agglomeration facilitates access to some infrastructures and to benefits generated from variety and specialisation, due to increased accessibility to a wide range of products and services from very different industries.[5] Advantages such as accessibility to real estate services and amenities (Buczkowska and De Lapparent 2014) attract new businesses, as these infrastructures provide services to firms and to managers/workers. Matching mechanisms connect individuals, firms, and organisations, enhancing their productivity levels, and increased city size facilitates these processes, since the chances of matching increase, as do the quality of the matches found. This is why high-tech firms prefer to locate in densely populated areas (Egeln, Gottschalk, and Rammer 2004) in order to benefit from the amenities located there; similarly, diversity tends to be higher in areas where the foreign-born population is higher, which fosters innovation and creativity (Lee, Florida, and Acs 2004). In this regard, as such amenities also push up wages (Roback 1982), and contribute to attracting high-skilled individuals, such as those working in high-tech industries. Learning mechanisms

[4]Nevertheless, there are also researchers who play down the role of agglomeration economies (see Rousseau 1995) and consider that skilled labour availability and sectorial specialisation are more important determinants of efficiency differentials at big urban areas.

[5]Nevertheless, urban size is not the only source of efficiency gains, as shown by the concept of 'borrowed size' (Alonso 1973). According to this, proximity to big cities may allow smaller cities to borrow some of the advantages of their bigger neighbours.

push up knowledge generation and dissemination inside a given area. These mechanisms are, for instance, captured by the existence of knowledge-based infrastructures, since new high-tech firms are hypothesised to locate close to universities and research centres in order to have better access to knowledge spillovers (Audretsch, Lehmann, and Warning 2005) and skilled labour, which is a key input for high-tech firms (Woodward, Figueiredo, and Guimarães 2006; Egeln, Gottschalk, and Rammer 2004). Similarly, high-tech firms prefer to locate inside high-tech districts, such as the 22@ district in Barcelona (Viladecans-Marsal and Arauzo-Carod 2012).

In addition to the previous mechanisms, there are additional characteristics to be considered, since socioeconomic conditions also matter (for example, labour market structure and participation in local elections). The attractiveness of an area is diminished by high unemployment rates (Egeln, Gottschalk, and Rammer 2004) and political support to right/left-wing parties also plays a role on the attractiveness of an area for new businesses (Nyström 2008).

In terms of analyses that explore how spatial specificities may influence firms' location decisions there is one crucial point, which is the selection of the spatial unit to be used. A medium-term analysis on this topic shows that research on spatial units have moved from large ones in the 1980s, to smaller ones in the present day. Specifically, papers published in the eighties and nineties commonly used large geographical areas, such as states in the U.S (Friedman, Gerlowski, and Silberman 1992), when analysing firm location decisions (although there were also analyses that referred to smaller (functional) units such as U.S. metropolitan areas (Carlton 1983)). Later, smaller administrative areas were introduced, such as counties (List 2001) and municipalities (Arauzo-Carod 2005). There is, however, no consensus on strategies since some researchers continue to use metropolitan areas (Arauzo-Carod and Viladecans-Marsal 2009) or municipalities (Buczkowska and De Lapparent 2014) as spatial units, while others use smaller areas focusing on what is happening inside cities. Such empirical applications as exist at the intra-urban level are mainly for Chinese cities, for example ones using the sub-district offices of Nanjing (Li and Zhu 2017), or the postal zones of Beijing (Zhang et al. 2013).

This shift from large areas to smaller ones has also generated analyses in which scholars have empirically tested the implications of using alternative spatial units. On that subject, Arauzo-Carod and Manjón-Antolín (2004) analysed location decisions at province, county and municipal level in Catalonia and concluded that using alternative geographical aggregation may bias results. Similarly, Arauzo-Carod (2008) uses the same dataset and, in addition to studying administrative units such as municipalities and counties, also analyses location decisions for functional units (i.e., travel-to-work areas). His results support previous findings in terms of potential bias if using available data without discussing whether the geographical aggregation is appropriated, and he concludes that the fit is better for municipalities.

Previous empirical contributions suggest, in general terms, that since key location determinants such as economies due to agglomeration are stronger at shorter areas and attenuate quickly with distance, it seems more appropriate to use small geographic areas (e.g., neighbourhoods) in order to capture their effect on entry decisions. Given these comments, it seems that the next step in location analysis should be to focus (when possible) on sub-units of large urban areas in order to take into account their internal heterogeneity. Unfortunately, as far as we are aware, contributions at intra-urban level for European countries are still scarce (see, for instance, Moriset 2003, for Lyon; Isaksen 2004, for Oslo).[6] Outside Europe, there are some papers on Turkey (Berkoz and Turk 2008, for Istanbul), Canada (Maoh and Kanaroglou 2007, for Hamilton), Japan (Arai et al. 2004, for Tokyo), Colombia (Moreno-Monroy and García Cruz 2016), Israel (Frenkel 2012), U.S. (Walcott 1999). Unsurprisingly, as urban growth and firm location processes have been of high importance for Chinese cities in recent years, most current contributions relate to these (Yuan et al. 2017,; Li and Zhu 2017, for Nanjing; Wei et al. 2016, for Shanghai; Li et al. 2015,; Zhang et al. 2013, for Beijing; Huang and Wei 2014, for Wuhan).

In terms of the high-tech industries targeted by this paper, most econometric analyses of the location decisions of these industries in Europe rely on wide geographical areas (e.g., Autant-Bernard, Mangematin, and Massard 2006, for the French regions) and, consequently, cannot account for firms' preferences for urban cores. We know that, traditionally, high-tech activities have been located at urban cores in search of the specialised services, human capital and knowledge flows that exist in these areas, and that peripheral areas cannot compete in attracting and/or generating such firms (Cooke 2004). That said, recent suburbanisation processes may alter the pattern, as the monocentric distribution of economic activity moves towards a polycentric one (Frenkel 2012).[7] In this sense, in countries such as the U.S., where suburbanisation started earlier, entries of high-tech firms (both for manufacturing and services) are higher in suburbs than in urban cores (Renski 2009). From a European perspective, though, the cores of big metropolitan areas still attract high-tech firms.[8] However, in some cases, Barcelona being a case in point, traditional cores are slowly moving to edge neighbourhoods.

In addition to previous concerns, when analysing the location determinants of new firms it is necessary to take into account, not only the characteristics of the area where firms are located, but also those of neighbouring areas (Arauzo-Carod and Manjón-Antolín 2012), as their characteristics also influence location decisions. These neighbouring site effects have been analysed by, among others, Alamá-Sabater *et al.* (2011) and Artal-Tur et al. (2012). All in all, previous empirical evidence suggests that it is important to control for both the direct and indirect effects (LeSage and Pace 2009) arising from nearby sites when analysing the location determinants of firms. Surprisingly, these spatial issues have been introduced only recently into location analyses and, although becoming increasingly popular, they are not yet standard.

It is clear that some of highlighted shortcomings related to location determinants have been partially controlled for in the literature. Unfortunately, this has been only partial and does not include all the dimensions that we have identified as relevant for this paper: the intra-urban one (i.e., city neighbourhoods), the industry one (i.e., high-tech industries) and the geographical one (i.e., continental Europe). This is the gap that the current paper aims to fulfil.

[6]Lack of empirical research for European cities is especially relevant in view of urban specificities across cities in different areas (e.g., Asian cities, U.S. cities, continental European cities, etc.) that make comparisons difficult.

[7]There is plenty of evidence of suburbanisation of high-tech activities. See, for instance, Nunn and Warren (2000) for computer services in the metropolitan statistical areas of the U.S. or Guillain, Le Gallo, and Boiteux-Orain (2006) for a wide range of industries at the Paris region.

[8]The attractiveness of large urban areas should be considered in net terms, as there are, as well, additional disagglomeration economies operating for these cities (Camagni, Capello, and Caragliu 2016).

3. Empirical strategy

3.1. Study area

Barcelona is a densely populated city (15,800 inhabitants per km^2), especially as compared to other big European capitals such as Rome (2,110), Berlin (3,852) or Warsaw (3,340). Although, in view of its attraction of high-tech firms, this paper focuses on the city of Barcelona, the results are relevant to many other European urban areas where similar factors apply.

3.2. Datasets

This paper uses two main data sources. The first one is the *Sistema de Análisis de Balances Ibéricos* (henceforth SABI) compiled by INFORMA D&B and Bureau Van Dijk, which contains data from the Spanish Mercantile Register. The SABI dataset contains exhaustive information on balance sheets at the firm level and has been extensively used for location analyses by many scholars.[9] The second dataset is the statistical service of Barcelona city council, which provides information about Barcelona's neighbourhoods.

Data from SABI includes detailed information at firm level such as location, number of employees, legal status and sales. Data is available at the 4-digit NACE level although, for our purposes, aggregation to the 3-digit level is more appropriate. Specifically, we analyse the location determinants of the 515 registered entries between 2011 and 2013 for the industries shown in Table 1.[10] In addition to these we include a group for the remaining firms (i.e., 6,234 entries from non-high-tech industries).

Data from the statistical service of Barcelona city council is provided for several aggregation levels: the whole city, 10 districts, 73 neighbourhoods, 233 basic statistic areas and 1,061 census districts. When selecting the level there is a trade-off between spatial disaggregation and the availability of data, in that the higher the disaggregation level, the fewer (and less reliable) the data collected by the city council. Therefore, for the purposes of this analysis (see Section 2 for details), we have decided to work at neighbourhood level (i.e., 73 units).

3.3. Variables and estimation

In the light of the previously stated concerns, our dependent variable is the location between 2011 and 2013, of new firms from the industries mentioned above. Specifically, the main dependent variables are defined as the count of new firms belonging to Video & TV Production (hereafter VIDEO), Wired Telecommunications and Other Telecommunications (hereafter TELECOMMUNICATIONS), Computer Programming & Consultancy and Data

Table 1. High-tech industries considered.

Industry	NACE code
Video & TV Production	591
Wired Telecommunications and Other Telecommunications	611, 619
Computer Programming & Consultancy, and Data processing & Hosting	620, 631
Other Information Services	639
R&D Natural Sciences & Engineering, and R&D Social Sciences & Humanities	721, 722

Source: author.

[9] See, among others, Jofre-Monseny and Solé-Ollé (2009) and Jofre-Monseny, Marín-López, and Viladecans-Marsal (2011).
[10] Selection is made according to both standard classifications of high-tech activities and the typology of industries predominant in Barcelona.

processing & Hosting (hereafter COMPUTER), Other Information services (hereafter INFORMATION), R&D Natural Sciences & Engineering and R&D Social Sciences & Humanities (hereafter R&D). These industries have been measured at the 3-digit level at each one of Barcelona's 73 neighbourhoods during the period 2011–2013. In addition to these high-tech industries, we include overall entries of firms belonging to the remaining industries (Non-high-tech).

As we assume that the competitiveness of urban cores (and their attractiveness for new high-tech firms) comes from a combination of social, economic, cultural and infrastructural factors (Kitson, Martin, and Tyler 2004), we need to take into account both economic and amenity-oriented determinants as explanatory variables. Consequently, these variables include several vectors related to *i)* agglomeration economies, *ii)* knowledge-based infrastructures, *iii)* socioeconomic conditions, *iv)* population, and *v)* real estate and amenities. These variables[11] are also calculated at the neighbourhood level, the reference year differs depending on each covariate, and some of them are spatially lagged. In order to tackle potential endogeneity several strategies have been used, such as lagging must of covariates (Cissé, Dubé, and Brunelle 2020), using spatial lags of some covariates (Piacentino et al. 2017), and using highly disaggregated spatial units as neighbourhoods (Holl 2004).[12] Regarding aforementioned vectors, first, agglomeration economies variables include the stock of firms of the same industry in 2010 (STOCK_*XX*) as well as the spatially lagged versions of them (W_STOCK_*XX*). Second, knowledge-based infrastructure variables include a dummy for the 22@ innovation district (DIST_22, an urban renewal project that is transforming a district that traditionally specialised in mature manufacturing activities) and the number of university faculties (FAC). Third, human capital variables include the spatial lag of the percentage of the population with college degrees or equivalent (W_COLLE). Fourth, socioeconomic conditions variables include the unemployment rate (UNE). Fifth, population variables include population (POP) and the percentage of foreigners in the total population (FORE). And sixth, real estate and amenities variables include commercial rental prices (COMP) in 2010 and density of stops of local buses (BUS).[13]

Focusing on the location phenomenon might generate a bias by excluding neighbourhoods not chosen by any firm. Concretely, the data for high-tech firms entering between 2011 and 2013 shows that 56 neighbourhoods out of 73 (76.7%) were chosen by at least one firm, but

[11]Following Babyak (2004) and in order to assess the (potential) impact of overfitting in our estimates, we have estimated different combinations of the estimations using a shorter number of covariates, and the results are essentially the same. Additionally, we checked AIC when adding/dropping parameters and although, in general terms, lower AIC were obtained when dropping out covariates (this effect was largely dependent on the specific covariates involved). Therefore, we consider that although overfitting is a relevant issue that has to be always monitored and controlled, in this case it is not driving results in a relevant way.

[12]See Alañón-Pardo and Arauzo-Carod (2013) and Melo, Graham, and Noland (2010) for an extended discussion.

[13]For the sake of making the econometric estimation as simple as possible (and in order to avoid potential problems of overfitting -see also footnote 11) we decided not to include spatial lags of all independent covariates (additionally, it was unnecessary to lag all of them because some variables did not have a clear spatial pattern as values at a given neighbourhood had no or minor relationship with values in near areas, according to Moran's I results). We selected stock of firms because of the expected spatial scope of agglomeration economies caused by the concentration of firms was expected to go beyond neighbourhood borders; 22@ district dummy, because of similar reasons, as although the official policies of 22@ target only this single district it is also true that many firms outside the 22@ may also benefit if they locate close to facilities existing there; population with college degree, because of well-known positive effects of human capital that are very difficult to constrain inside neighbourhood borders; and percentage of foreigners, because of benefits of a 'melting pot' imply a lot of amenities and economic activities occurring a limited distance from the neighbourhoods where foreigners live.

none chose the remaining 17 (23.3%). Any potential bias disappears when using a count data model (CDM) as this compute how many times each area (i.e., neighbourhood) was chosen by a firm, since those with zero occurrences are also relevant because their independent variable values explain why they were not been chosen by new firms.

When using a CDM to analyse location patterns there are two potential schemes (Arauzo-Carod 2005; Guimarães, Figueiredo, and Woodward 2003): *i)* which considers that location decisions are taken according to a vector of variables shared by all entrants ($z_{ij} = z_i$), and *ii)* which considers that location decisions are taken according to a vector of variables shared by groups of entrants ($z_{ij} = z_{ig}$ for $g = 1, 2, \ldots, G$, where G is the number of groups). In this paper grouping of entrants is done using the specific high-tech industry to which each firm belongs.

Concretely, we model location decisions at neighbourhood level with an exponential conditional mean function (Cameron and Trivedi 1998):

$$E[Y|X] = \mu = e^{W-X\beta}$$

where the dependent variable Y is a vector that contains the number of new firms located during a time period in one of the 73 neighbourhoods. This specification includes Poisson and Negative Binomial models that differ in the form of the conditional variance function (μ in the Poisson model and $\mu + \alpha\mu^2$ in the Negative Binomial model). Most of recent contributions that analyse firms' location determinants focusing on the characteristics of sites potentially selected by new firms rely on Count Data Models (CDM) (see Arauzo-Carod, Liviano-Solís, and Manjón-Antolín 2010, for an extensive review of the empirical literature). As the CDM family is quite large, in order to discriminate among alternative CDMs, we carried out several tests[14] that suggested using a Poisson model for estimation of VIDEO, TELECOMMUNICATIONS, INFORMATION and R&D industries and a Negative Binomial model for estimations of COMPUTER industries, all high-tech industries and non-high-tech industries.

We modelled the number of new high-tech firms in a neighbourhood as a function of the local specific characteristics previously described:

$$Y_{ij} = \beta X_j + \beta W X_j + \varepsilon_{ij}$$

where Y_{ij} is the number of new firms belonging to industry i located in a neighbourhood j, X_j includes the previously explained set of covariates, WX_j includes the spatially weighted average of neighbouring areas of most of the previous covariates (where W is a symmetric row-standardised contiguity matrix with elements taking values 1/0 depending on whether two areas are considered as neighbours, and X_j includes covariates with spatial variation), and ε_{ij} is an error term.

4. Empirical analysis

The empirical analysis includes a spatial exploratory analysis intended to identify spatial patterns regarding the entry of new firms, and an econometric analysis in order to identify location determinants.

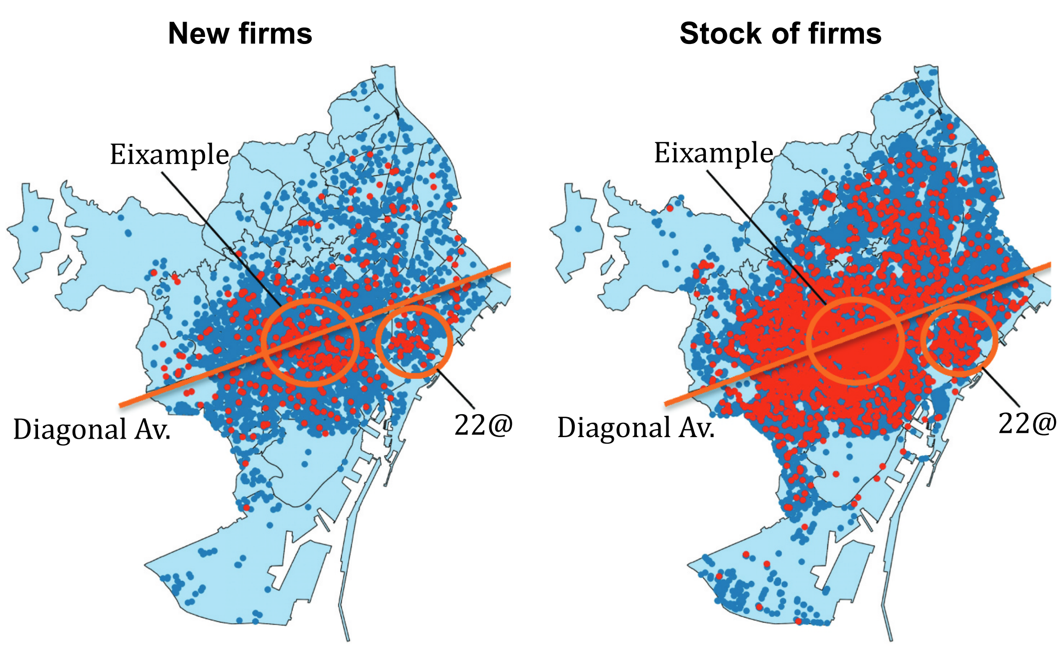
[14]Results of these tests (overdispersion, dispersion statistic, and alpha = 0) are available upon request. We have also carried out correlation analysis and there are no relevant issues with the selected variables.

An overview of the dependent variable of each industry at neighbourhood level (firm entry) shows that there is an important heterogeneity in terms of the number of firms entering Barcelona's neighbourhoods in the period. Specifically, 515 new firms entered in the selected high-tech industries, most of them (345) belonging to the COMPUTER industry, followed by VIDEO (84), and smaller numbers in the R&D (39), TELECOMMUNICATIONS (29) and INFORMATION industries (18.)

The agglomeration of entries at industry level is related to the total number of firms. This is why industries for which there is a low number of entries, agglomerate also into a small number of neighbourhoods (INFORMATION industries locate in only 13 neighbourhoods out of the 73 with R&D in 18 and TELECOMMUNICATION in 19), whilst those with a larger number of entries spread across most of the city (COMPUTER industries in 49 neighbourhoods and VIDEO in 34 neighbourhoods).

4.1. Spatial exploratory analysis

The total entries of high-tech firms between 2011 and 2013 (Figure 1) are clearly clustered around Barcelona's main axis, the Diagonal Avenue, and the central business district (CBD) known as the *Eixample*, with significant numbers also in the 22@ district. This pattern is due to the high concentration of facilities, public services and firms around this area. On the contrary, entries of non-high-tech firms are spread throughout the city, including peripheral neighbourhoods.



- High-tech firms
- Non high-tech firms

Source: author with data from SABI.

Figure 1. Firm entries (2011–2013) and firm stock (2010).

There is also some path dependence in terms of the neighbourhoods preferred by firms, in that the spatial distribution of the stock of high-tech and non-high-tech firms (2010) is quite similar. In general terms, both figures show that, for high-tech firms, CBD areas are preferred rather than peripheral ones, where high-tech entries are very scarce. These exploratory results corroborate those of Arai et al. (2004) for Tokyo, but they differ from those found by Frenkel (2012) for the Tel Aviv metropolitan region. In any case, there is wide evidence for high-tech firms clustering in European cities suggesting the importance of interactions among firms (Arbia et al. 2012),[15] which is facilitated if firms locate close together.

Data about entries allow some indicators to be calculated related to similarity/dissimilarity of neighbourhoods in terms of the type of industries that tend to locate there. Among these indicators we will concentrate on the Gini Index (Duncan and Duncan 1955) and the Entropy Index (Theil 1972).

Firstly, the Gini Index (*G*) allows a more detailed analysis, as each industry is analysed in a separate way, so that we may obtain an indicator about whether a specific industry is equally distributed across a given number of neighbourhoods. *G* ranges between 0 and 1, with values close to 0 indicating that industry *x* has roughly the same weight across all neighbourhoods, whilst values close to 1 indicate that the weight differs considerably across them. Table 2 provides results of *G* both for the entries (2011–2013) and the stock of firms (2010), which suggest that the stock of incumbent firms tend to be more homogeneously distributed than that of entries, especially for the INFORMATION and TELECOMMUNICATION industries.[16]

Table 2. Asymmetries of stock/entries (Gini index).

Industry	Entries (2011–2013)	Stock (2010)
Video & TV Production	0.4727	0.3044
Wired Telecommunications and Other Telecommunications	0.6551	0.3743
Computer Programming & Consultancy, and Data processing & Hosting	0.2856	0.1992
Other Information Services	0.7118	0.1875
R&D Natural Sciences & Engineering, and R&D Social Sciences & Humanities	0.5733	0.4743
High-tech (altogether)	0.2687	0.1389

Note: Gini index has been calculated related to total stock/entries of firms.
Source: author using Geo-Segregation Analyzer (Apparicio et al. 2014).

Secondly, the Entropy Index (*E*) allows us to identify whether a neighbourhood is homogeneous or diverse. As usual, *E* ranges between 0 and 1, with values close to 0 indicating that there is a predominant activity (e.g., industry) in that area, and values close to 1 indicating that relative weights of each activity are quite similar. Figure 2 shows that areas with lower entropy levels tend to be the peripheral ones, whilst in core areas the distribution of high-tech industries is quite balanced.[17]

[15]This clustering pattern at core areas is also observed for other 'similar' industries, as advanced services in Brussels (Waiengnier et al. 2020).
[16]It is important to take into account that high levels of Gini index are partially explained by the few numbers of entries for these industries.
[17]As for the Gini index (see previous footnote), the lower entropy levels seem to be explained by a few entries at peripheral neighbourhoods.

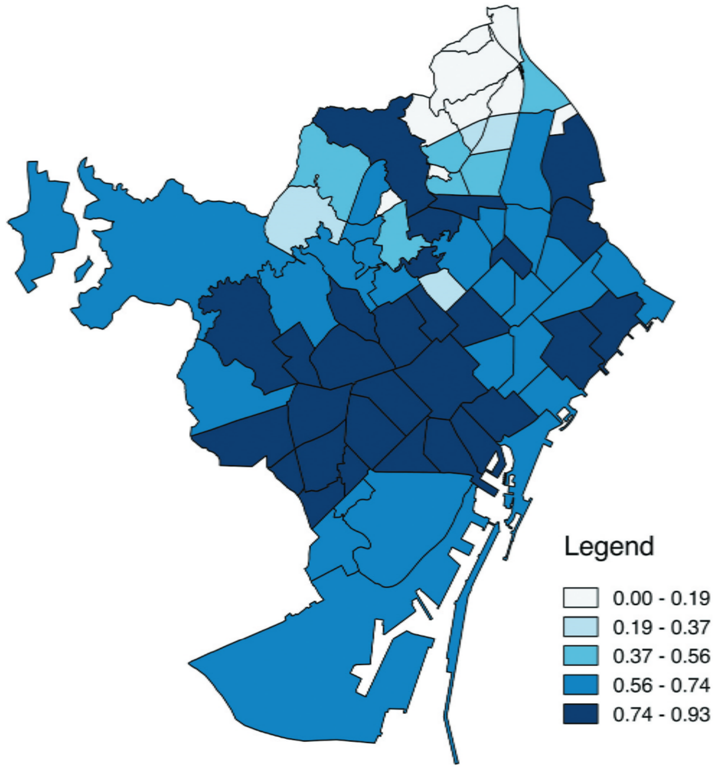


Figure 2. Entropy index for stock of high-tech firms (2010). Note: Entropy is calculated in terms of stock for each high-tech industry related to total stock of high-tech firms. Source: author using Geo-Segregation Analyser (Apparicio et al. 2014).

Although these figures indicate that there is some spatial clustering, this should be checked rigorously. Results from the spatial autocorrelation (Moran 1948) of the high-tech (non-high-tech) entries show a Moran's I of 0.381 (0.409), which implies that there is some (moderate) spatial autocorrelation of entries of new firms, implying that the number of entries at neighbourhood level is correlated with neighbouring area entries, although the spatial autocorrelation is slightly stronger for incumbent high-tech (0.414) and non-high-tech firms (0.424). In general terms, it seems reasonable to expect higher spatial autocorrelation levels for incumbent than for entering firms, because the former refers to a longer series of cumulated phenomena, whilst the later are about a shorter period, though these differences may also suggest that entries explore alternative areas through the city, and do not agglomerate solely at the traditional cores. Nevertheless, as this spatial autocorrelation may exist only in certain areas but not for the whole city, we have also calculated a Local Index of Spatial Association (LISA) (Anselin 1995).[18]

LISA results (Figure 3) show that spatial autocorrelation in Barcelona exists mainly at the central and peripheral areas in terms of entries and incumbent firms. In this respect,

[18]In order to calculate local and global measures of spatial autocorrelation, as well as spatially lagged variables, and in view of the size, shape and proximity of neighbourhoods of Barcelona, we have decided to use a contiguity matrix as a spatial weight matrix. Although there are alternative criteria (e.g., distance-based), these could have some limitations such as an inappropriate number of neighbours (i.e., very similar to that of total neighbourhoods).

in central areas (i.e., districts at the geographical and economic core of the city) there is a high-high significant local spatial autocorrelation (i.e., red areas), whilst in some peripheral areas (i.e., districts at the North-East end of the city) there is a low-low significant local spatial autocorrelation (i.e., dark blue areas). High-high local spatial autocorrelation indicates that neighbourhoods with a high number of entries (incumbents) are surrounded by other neighbourhoods with similarly high levels, whilst low-low local spatial autocorrelation indicates that neighbourhoods with low number of entries (incumbents) are surrounded by other neighbourhoods with similarly low levels.

4.2. Results

The location of new firms from each one of the selected high-tech industries is explained in terms of the effects of covariates belonging to seven vectors (agglomeration economies; knowledge-based infrastructures; human capital; socioeconomic conditions; population; real estate and amenities, and social participation). Our estimation strategy consists of separate regressions at industry level using the same set of covariates: *i)* a baseline specification of high-tech firms, non-high-tech firms and high-tech firms at industry level (Table 3) and *ii)* the same specification as in *i)* but adding some spatial lagged covariates (Table 4).

Table 3 shows industry-specific results for high-tech and non-high-tech activities. At first glance, these results suggest that: *i)* there are important similarities across high-tech industries in terms of the economic and social environment required in order to locate a new firm; *ii)* knowledge-based infrastructures and real estate and amenities are, by far, the most relevant location determinants for new firms; and *iii)* there are industry-specific patterns in terms of location behaviour, as the industries considered are not affected in the same way by selected covariates.

In terms of the specificities of location determinants for each industry the results show, generally speaking, that whilst for R&D entries the covariates are highly significant and help to explain location processes, for the rest of industries the explanatory power of the econometric specification is lower. This suggests that using the same specification for all industries is perhaps not the most appropriate strategy, as some of them could be affected by covariates not included in this analysis, but we have preferred to keep it for the sake of comparison across industries.

In terms of the effect of each group of covariates, knowledge-based infrastructures have, in general terms, a clear and positive effect over entries, whilst real estate and amenities act in the opposite way. Concretely, agglomeration economies are negative for most of industries, but only significant for R&D. This result is not in line with the majority of existent empirical evidence (see, among others, Li and Zhu 2017; Zhang et al. 2013; Arauzo-Carod and Viladecans-Marsal 2009; Woodward, Figueiredo, and Guimarães 2006) and suggests that in spite of processes in which industries tend to agglomerate at the CBDs of urban areas (Gorman 2002), there is some kind of deconcentration (perhaps suburbanisation), in which traditional cores are being replaced by new areas. This is a quite relevant result pointing out that although agglomeration economies persist, they may be quite dynamic from a geographical point of view and not always operating in the same areas. Traditionally, knowledge-based infrastructures have traditionally been identified as key inputs for innovative firms (Romijn and Albu 2002),

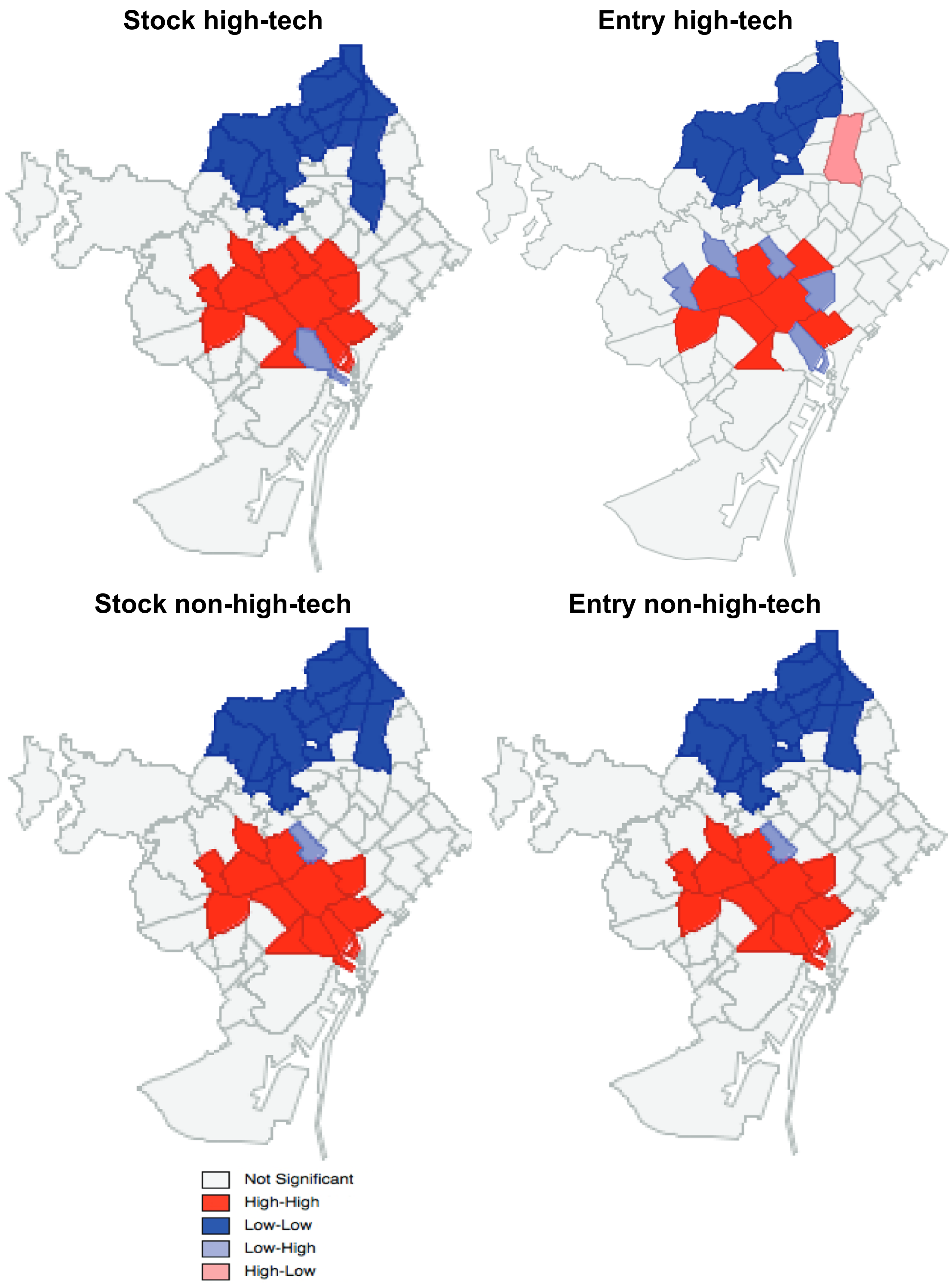


Figure 3. Local Spatial Autocorrelation (LISA) for firm entry (2011–2013) and stock (2010). Source: author with data from SABI.

although these have mainly been measured at a broader spatial level (Audretsch, Lehmann, and Warning 2005). In addition, it is not easy to capture the spatial linkages between start-ups and these infrastructures and therefore, the (expected) positive role of spatial proximity (Topa and Zenou 2015). In this case, the positive effect is explained

Table 3. High-tech (HT) and Non-high-tech (Non-HT) industries estimation (non-spatial).

Variables	HT	Non-HT	VIDEO	TELECOM.	COMPUTER	INFORM.	R&D
Agglomeration economies							
STOCK_*XX*	−0.000763	2.08e-05	−0.0134	−0.0144	−0.00301	0.00401	−0.277**
	(0.00264)	(0.000155)	(0.00982)	(0.0604)	(0.00670)	(0.0107)	(0.111)
Knowledge-based infrastructures							
DIST_22	1.191	1.602**	1.360***	1.396***	1.096	1.423**	1.370**
	(0.739)	(0.690)	(0.305)	(0.503)	(0.798)	(0.610)	(0.573)
FAC	0.112	0.153	0.0243	0.0844	0.103	0.0249	0.331**
	(0.126)	(0.106)	(0.0639)	(0.0970)	(0.133)	(0.141)	(0.129)
Socioeconomic conditions							
UNE	−0.0670	0.0315	−0.0443	−0.141	−0.0919	−0.0991	0.128
	(0.0854)	(0.0713)	(0.0489)	(0.0995)	(0.0926)	(0.106)	(0.0816)
Population							
POP	1.84e-05	2.30e-05	2.05e-06	1.82e-05	2.10e-05	−2.47e-05	4.10e-05***
	(1.58e-05)	(1.48e-05)	(9.08e-06)	(1.68e-05)	(1.73e-05)	(2.28e-05)	(1.29e-05)
FORE	−0.00188	−0.000631	−0.00514	0.0130	−0.00497	0.00677	−0.0206**
	(0.00830)	(0.000750)	(0.00665)	(0.0110)	(0.00899)	(0.0137)	(0.00969)
Real estate and amenities							
COMP	−0.00110	−0.000790	0.000765	−0.00154	−0.00127	−0.000382	0.000604
	(0.00111)	(0.000942)	(0.000667)	(0.00137)	(0.00124)	(0.00155)	(0.00114)
BUS	−5.280***	−3.446**	−3.590**	−4.597	−6.540***	−3.168	−8.093***
	(1.853)	(1.657)	(1.536)	(3.094)	(2.117)	(3.434)	(2.898)
Constant	3.528**	4.274***	0.264	0.896	3.760**	0.0615	−2.002
	(1.527)	(1.318)	(0.942)	(1.815)	(1.763)	(2.080)	(1.622)
lnalpha	0.442**	0.304**			0.527**		
	(0.194)	(0.150)			(0.215)		
Observations	73	73	73	73	73	73	73
Pseudo R2	0.0430	0.0276	0.135	0.169	0.0522	0.127	0.169
ll	−202.5	−379.5	−115.6	−52.76	−173.2	−42.50	−70.85

Notes: STOCK_*XX* corresponds to stock of firms of the industry of each estimation.
Source: author's estimates, standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

mainly by the dummy variable for 22@ district (DIST_22), which has a positive and significant effect for all high-tech industries but COMPUTER industries. Although the 22@ district attracts different type of firms, its effect differs considerably at industry level. In this sense, being inside the Barcelona's hi-tech district (i.e., 22@) increases the expected number of entries by 396.5% for the aggregated Non-high-tech industries, whilst for the aggregated High-tech industries although the coefficient is positive, it is not significant. As for the specific high-tech industries, results are as well large but lower than for Non-high-tech industries: VIDEO (289.7%), TELECOMMUNICATIONS (303.9%), COMPUTER (199.1%), INFORMATION (314.9%), R&D (293.4%). These results suggest that 22@ district is not only about technology, but that this area attracts a wide range of activities (both related and unrelated to high-tech ones) thanks to its important dynamism. Locating in this area is not only explained by face-to-face interactions with relevant firms and stakeholders (Arzaghi and Henderson 2008), but by firms' preferences to locate in prestigious areas where, they also benefit from a dense network of high-tech firms, better telecommunication infrastructures, larger diversity of specialised suppliers, and a continuous increase in the availability of new office spaces – despite the higher rents (Waiengnier et al. 2020). It should be noted that this area is still quite diverse in terms of the profile of firms located there (there is an ongoing process of transformation from mature industries to high-tech ones which is still active), and that the borders of the 22@ district are not yet clearly defined.

Table 4. High-tech (HT) and Non-high-tech (Non-HT) industries estimation (spatial).

Variables	HT	Non-HT	VIDEO	TELECOM.	COMPUTER	INFORM.	R&D
Agglomeration economies							
STOCK_*XX*	−0.000193	5.84e-05	−0.00258	0.0262	−0.00238	0.0115	−0.272**
	(0.00225)	(0.000134)	(0.00941)	(0.0704)	(0.00568)	(0.0122)	(0.117)
Knowledge-based infrastructures							
DIST_22	1.980***	2.304***	1.849***	2.469***	2.006**	2.519***	3.195***
	(0.734)	(0.700)	(0.350)	(0.682)	(0.814)	(0.859)	(0.747)
FAC	0.0675	0.119	0.0143	0.129	0.0680	0.0493	0.296**
	(0.117)	(0.105)	(0.0639)	(0.0981)	(0.122)	(0.142)	(0.129)
Socioeconomic conditions							
UNE	0.0442	0.140*	0.0187	−0.0622	0.0132	−0.0388	0.350***
	(0.0911)	(0.0819)	(0.0565)	(0.118)	(0.0982)	(0.128)	(0.109)
Population							
POP	4.21e-06	8.91e-06	−9.22e-06	4.95e-06	7.96e-06	−4.37e-05	2.99e-05**
	(1.56e-05)	(1.44e-05)	(1.02e-05)	(2.04e-05)	(1.67e-05)	(2.71e-05)	(1.51e-05)
FORE	−9.18e-05	0.000166	−0.00510	0.0215*	−0.00413	0.0185	−0.0256**
	(0.00760)	(0.00708)	(0.00711)	(0.0129)	(0.00826)	(0.0161)	(0.0107)
Real estate and amenities							
COMP	0.000188	9.27e-05	0.00121*	−0.00227	0.000155	−0.000518	0.00162
	(0.00112)	(0.00105)	(0.000730)	(0.00164)	(0.00126)	(0.00172)	(0.00130)
BUS	−5.262**	−2.623	−3.618**	−6.102*	−6.923***	−4.173	−10.02***
	(2.065)	(1.984)	(1.645)	(3.330)	(2.333)	(3.803)	(3.478)
Spatially lagged variables							
W_STOCK_*XX*	−0.0365**	−0.0168	−0.0360***	−0.0587**	−0.0370**	−0.0610**	−0.112***
	(0.0150)	(0.0138)	(0.00987)	(0.0238)	(0.0159)	(0.0300)	(0.0290)
W_COLLE	0.0513***	0.0397***	0.0475***	0.0456**	0.0463***	0.0672**	0.107***
	(0.0165)	(0.0146)	(0.0117)	(0.0196)	(0.0169)	(0.0342)	(0.0239)
Constant	0.705	1.583	−1.259	0.196	1.089	−1.233	−6.886***
	(1.803)	(1.665)	(1.183)	(2.325)	(2.031)	(2.640)	(2.247)
lnalpha	0.269	0.212			0.355		
	(0.205)	(0.152)			(0.228)		
Observations	73	73	73	73	73	73	73
Pseudo R2	0.0652	0.0381	0.197	0.227	0.0735	0.172	0.294
ll	−197.8	−375.4	−107.3	−49.07	−169.3	−40.29	−60.16

Notes: STOCK_*XX* and W_STOCK_*XX* correspond, respectively, to stock of firms of the industry of each estimation and to spatially lagged stock of firms of the industry of each estimation.
Source: author's estimates, standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1

It is clear that the variable capturing university facilities (FAC) has little effect on attracting high-tech firms (this only being significant for R&D), but there is empirical evidence suggesting that there are important heterogeneities depending on universities' profile (Di Gregorio and Shane 2003) that shape the way in which such public infrastructures may attract new firms. There is no consensus on this in the literature since, in some studies on the location determinants of high-tech firms (e.g., Zhang et al. 2013, for Beijing) the effect of the availability of universities and research institutions is clearly positive but, conversely, in others (e.g., Li and Zhu 2017, for Nanjing) location increases with distance to the nearest university.

Population has been identified as an important agglomeration force attracting new firms, including high-tech ones (Egeln, Gottschalk, and Rammer 2004). Here, we should remark that, except for some neighbourhoods in the upper side of the city, most of Barcelona has a mixture of both residential and economic activities, densely populated areas also being attractive for firms in view of their retail services and public transportation facilities. Socioeconomic conditions seem to be less important for location decisions. In this sense, we hypothesise that unemployment (UNE) may act as a barrier to entries because it may discourage potential firms by signalling less dynamic neighbourhoods (Egeln, Gottschalk, and Rammer 2004), but as our results are not significant for any industry (although the coefficient has the expected negative sign for most of them), it could be reasonable that being that Barcelona is a single labour market (and even the whole metropolitan area), trying to capture these effects at a very detailed spatial level is not a correct strategy.

In terms of real estate and amenities, the results are quite mixed. We find that *i)* real estate commercial prices (COMP) have an unclear effect as they do not reduce entries for any industry,[19] and that *ii)* availability of public transport stops (BUS) deter entry, surely indicating a tough competition for space between residential and economic activities (in a similar way, Gabriel and Rosenthal (2004), highlight the different preferences of households and firms in terms of location).[20]

Nevertheless, as the previous results do not include spatial effects, we consider that one should take into account, not only the characteristics of the areas where new firms locate, but also those of their neighbouring areas. Accordingly, Table 4 shows the same estimation as in Table 3 but including spatial lagged variables for some covariates.[21] In addition to the previous general results, those of Table 4 indicate that spatial spillovers are relevant for location decisions as firms consider not only the characteristics of the areas where they do locate but also the ones of close neighbourhoods.

When spatially lagged variables are introduced, the fit improves for all estimations and most of previous variables maintain the same sign and significance, although some effects are now captured by the new variables. In general terms, it is noticeable that i) similarly to what happens to the stock of firms in the same neighbourhood, the stock of firms of the same industry in neighbouring areas (W_STOCK_XX) has a negative and significant effect for all specifications but the one of Non-high-tech industries, suggesting (as in previous estimation) that geography of local specialisation may be changing; that ii) when controlling for what happens in geographically close areas, the effect of 22@ district becomes significant for all specifications; and that iii) the educational level in neighbouring areas (W_COLLE) has the expected positive and significant effect for all the industries (see Arauzo-Carod 2013 for a detailed analysis for Catalan cities). In this sense, it is important to notice that skilled workers tend to agglomerate at urban cores (Combes, Duranton, and Gobillon 2008), which favours high-tech entries (but also entries for other types of firms) in these areas.

Overall, our results help to illustrate how the location decisions of high-tech firms are shaped by the characteristics of city neighbourhoods. Nevertheless, the covariates used in

[19] Despite coefficients were non-significant, they had a negative sign in most specifications. In this sense, a similar analysis for Beijing postal areas (Zhang et al. 2013) shows that land prices deter entry of high-tech firms.

[20] Although there is theoretical and empirical evidence suggesting the positive relationship between amenities and wages (Roback 1982), the identification of such amenities (and its inclusion in an econometric estimation) is not obvious. Notwithstanding these difficulties, our variable measuring availability of the public bike renting system captures some amenities as public transport accessibility that are expected to be positively appreciated by workforce of high-tech firms. At this point, our approach is similar to the one known as 'voting-with-your-feet', initially proposed by Tiebout (1956) and later on developed by, among others, Wall (2001). Concretely, this approach implies that location decisions are taken depending on the trade-off between advantages and costs of different sites (e.g., amenities vs. local taxes), being that agents (e.g., firms) will move away if they feel that, for instance, quality of local amenities does not deserve the costs of locating there.

[21] Fort the sake of simplicity, we did not include the spatial lagged counterparts of all covariates, as the spatial scope of the omitted ones is not expected to go beyond a neighbourhood's borders. See also footnotes 11 and 14.

this paper do not fully explain the whole decision process as some variables are undoubtedly be omitted and there are (potentially) random processes affecting all location decisions.

4.3. Robustness

The robustness of the results is tested according to different model specifications and is shown in Tables A.1 and A.2. In particular, Table A.1 includes the same specification discussed in Section 4.2 but with robust standard errors, and Table A.2 shows an alternative specification using alternative independent variables. Concretely, the variables for Table A.2 are changed as follows: i) population (now we use the density of population -POPD- instead of the stock), ii) real estate (commercial prices of 2010 are now measured using selling prices -COMPS- instead of rentals), iii) knowledge-based infrastructures (the stock of university faculties is replaced by a dummy -FACD- indicating if there is a faculty at the neighbourhood.

We find that, when using robust standard errors, the new results roughly mimic the previous ones, except for some specifications in which the significance levels are higher. And as for the alternative independent variables, the coefficient estimates are remarkably stable as new results are quite similar to previous ones except, partially, the ones referred to knowledge-based infrastructures, that now increase their significance. To sum up, these robustness estimations corroborate the previous results and validate in general terms the role played by the location determinants identified in the previous section. Finally, in addition to these robustness strategies we calculated our preferred specification clustered at district level, and again, found few changes.[22]

5. Conclusions

This paper analyses the location determinants of high-tech firms but, as opposed to previous contributions that rely on bigger areas such as metropolitan areas or municipalities, it focuses on the intra-urban level. Specifically, we use data from high-tech firms entering neighbourhoods of Barcelona, and we contribute to the empirical literature by providing evidence showing that these firms tend to agglomerate in some core areas of the city, rather than to homogeneously distribute across neighbourhoods. Networking opportunities and location in prestigious areas are key locational determinants that boost the attractiveness of central areas, which benefit from public efforts promoting them, as in the case of the 22@ district.[23] At the same time, our results suggest that, within a city known for prestigious high-tech activities, firms do care about precisely where to locate, which implies that not all neighbourhoods will benefit equally. As to previous stated, this paper fills a gap in the empirical literature by carrying out an analysis that takes into account several dimensions which, until now, had been only partially considered. Namely, *i)* the intra-urban geographical scope, *ii)* the specificities of high-tech industries and, *iii)* the neighbouring effects.

[22]Each of the 73 neighbourhoods of Barcelona belongs to one of the 10 city districts. Results clustered at district level are available on request.

[23]These public efforts include, among others, the creation of research and innovation centres and the relocation of several public university facilities.

Based on our results, mainly those in regard to the important role played by knowledge-based infrastructures, real estate and amenities, agglomeration economies and the industry specificities, some interesting policy implications arise. Firstly, the intra-urban level is appropriate for analysing firms' entry decisions. This is an important point, as it implies that neighbourhood characteristics matter, so public administrations should take them into account when designing policies to attract firms. At the same time, this is a very controversial issue since it implies strategically focusing public funds and promotional efforts onto particular areas of the city, rather than disseminating them more widely. In order to avoid the potential negative effects of these decisions, city councils should carefully analyse the potential of each area and try to promote them considering potential benefits. Secondly, long-term tech-promoting policies, such as the one carried out in the 22@ district, may have a remarkable effect in terms of attracting high-tech firms to targeted areas, so policy strategies do matter for attracting firms. In addition, these policies need to involve some degree of public-private cooperation processes, as development of these areas is in both their interests.

Regarding the limitations of this paper, firstly, one may argue against using the same specification for all industries in view of their specificities, but we preferred this strategy for the sake of comparison across industries; secondly, focusing on the intra-urban level allowed more accurate results but, since few studies exist at this spatial level, largely barred us from comparison with similar studies; and thirdly, although potential endogeneity issues could threat the credibility of paper's findings, we have addressed them by lagging all covariates, adding spatial lags of some covariates and using highly disaggregated spatial units.

There are several issues that are beyond the scope of this analysis and are left for future research: the first one is whether the effects of covariates vary across each neighbourhoods; the second is to explore whether location patterns and the effects of location determinants hold for different firm sizes; the third one is whether spatial interactions are inversely related with physical distance or if, on the contrary, start-ups can interact equally well with institutions and amenities located in more distant areas (Topa and Zenou 2015); and the fourth one refers to a potential change in location patterns suggesting that attracting urban cores may be changing.

Acknowledgments

This research was partially funded by FEDER/Ministerio de Ciencia, Innovación y Universidades – Agencia Estatal de Investigación ECO2017-88888-P, the "Xarxa de Referència d'R+D+I en Economia i Polítiques Públiques" and the SGR Program (2017-SGR-159) of the Generalitat de Catalunya. I would like to acknowledge research assistance by M. Lleixà, supportive comments by A. Rodríguez-Posse, M. Manjón-Antolín, seminar and conference participants, and two anonymous referees, for their valuable comments and suggestions.

Disclosure of potential conflicts of interest

No potential conflict of interest was reported by the author(s).

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Appendices

Table A1. (robustness check): High-tech (HT) and Non-high-tech (Non-HT) industries estimation (spatial) (with robust standard errors).

Variables	HT	Non-HT	VIDEO	TELECOM.	COMPUTER	INFORM.	R&D
Agglomeration economies							
STOCK_*XX*	−0.000193	5.84e-05	−0.00258	0.0262	−0.00238	0.0115	−0.272**
	(0.00158)	(9.76e-05)	(0.0102)	(0.0697)	(0.00359)	(0.00865)	(0.135)
Knowledge-based infrastructures							
DIST_22	1.980***	2.304***	1.849***	2.469***	2.006***	2.519**	3.195***
	(0.672)	(0.852)	(0.562)	(0.754)	(0.766)	(1.105)	(1.023)
FAC	0.0675	0.119	0.0143	0.129	0.0680	0.0493	0.296***
	(0.0994)	(0.0865)	(0.0812)	(0.109)	(0.0881)	(0.0989)	(0.106)
Socioeconomic conditions							
UNE	0.0442	0.140**	0.0187	−0.0622	0.0132	−0.0388	0.350***
	(0.0795)	(0.0694)	(0.0584)	(0.0992)	(0.0804)	(0.0955)	(0.126)
Population							
POP	4.21e-06	8.91e-06	−9.22e-06	4.95e-06	7.96e-06	−4.37e-05*	2.99e-05*
	(0.1.35e-05)	(1.41e-05)	(1.31e-05)	(1.72e-05)	(1.31e-05)	(2.30e-05)	(1.59e-05)
FORE	−9.18e-05	0.000166	−0.00510	0.0215	−0.00413	0.0185	−0.0256**
	(0.00858)	(0.00749)	(0.0112)	(0.0160)	(0.00901)	(0.0169)	(0.0115)
Real estate and amenities							
COMP	0.000188	9.27e-05	0.00121	−0.00227	0.000155	−0.000518	0.00162
	(0.000881)	(0.000883)	(0.000882)	(0.00155)	(0.00108)	(0.00159)	(0.00129)
BUS	−5.262***	−2.623	−3.618	−6.102**	−6.923***	−4.173	−10.02**
	(1.776)	(1.766)	(2.525)	(3.052)	(1.958)	(4.170)	(4.185)
Spatially lagged variables							
W_STOCK_*XX*	−0.0365***	−0.0168	−0.0360***	−0.0587**	−0.0370**	−0.0610*	−0.112***
	(0.0140)	(0.0154)	(0.0137)	(0.0291)	(0.0147)	(0.0335)	(0.0362)
W_COLLE	0.0513***	0.0397***	0.0475***	0.0456***	0.0463***	0.0672*	0.107***
	(0.0139)	(0.0145)	(0.0151)	(0.0186)	(0.0135)	(0.0393)	(0.0320)
Constant	0.705	1.583	−1.259	0.196	1.089	−1.233	−6.886***
	(1.350)	(1.277)	(1.414)	(1.603)	(1.631)	(2.276)	(2.611)
lnalpha	0.269	0.212			0.355		
	(0.188)	(0.138)			(0.231)		
Observations	73	73	73	73	73	73	73
Pseudo R2	0.0652	0.0381	0.197	0.227	0.0735	0.172	0.294
ll	−197.8	−375.4	−107.3	−49.07	−169.3	−40.29	−60.16

Notes: STOCK_*XX* and W_STOCK_*XX* correspond, respectively, to stock of firms of the industry of each estimation and to spatially lagged stock of firms of the industry of each estimation.
Source: author's estimates, robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1

Table A2. (robustness check): High-tech (HT) and Non-high-tech (Non-HT) industries estimation (spatial) (with alternative independent variables).

Variables	HT	Non-HT	VIDEO	TELECOM.	COMPUTER	INFORM.	R&D
Agglomeration economies							
STOCK_XX	1.11e-05	5.39e-05	−0.00961	0.0569	−0.00158	0.000414	−0.262**
	(0.00207)	(0.000130)	(0.0107)	(0.0577)	(0.00523)	(0.0133)	(0.131)
Knowledge-based infrastructures							
DIST_22	1.692**	1.824**	1.838***	2.817***	1.676**	2.444***	2.798***
	(0.734)	(0.728)	(0.368)	(0.744)	(0.812)	(0.937)	(0.734)
FACD	0.421	0.487	0.685**	0.906**	0.414	1.307**	1.072**
	(0.523)	(0.517)	(0.297)	(0.462)	(0.568)	(0.645)	(0.519)
Socioeconomic conditions							
UNE	0.0548	0.146*	0.0306	−0.0728	0.0378	−0.0403	0.357***
	(0.0921)	(0.0848)	(0.0634)	(0.121)	(0.102)	(0.164)	(0.110)
Population							
POPD	0.000472	0.000551	0.00115	−0.00135	0.000441	0.00128	0.00196
	(0.00131)	(0.00125)	(0.000903)	(0.00151)	(0.00142)	(0.00195)	(0.00150)
FORE	−0.00291	−0.00324	−0.00805	0.0129	−0.00721	0.00483	−0.0277**
	(0.00841)	(0.00784)	(0.00701)	(0.0139)	(0.00901)	(0.0158)	(0.0110)
Real estate and amenities							
COMPS	0.000126	0.000259	0.000194	−0.00121**	0.000240	−0.000407	0.00118*
	(0.000472)	(0.000440)	(0.000315)	(0.000510)	(0.000516)	(0.000701)	(0.000621)
BUS	−5.284***	−2.899	−3.341*	−6.977**	−6.864***	−4.467	−8.021**
	(2.046)	(1.969)	(1.721)	(3.496)	(2.318)	(3.885)	(3.218)
Spatially lagged variables							
W_STOCK_XX	−0.0374***	−0.0199	−0.0358***	−0.0727***	−0.0395**	−0.0571**	−0.127***
	(0.0145)	(0.0135)	(0.0104)	(0.0243)	(0.0157)	(0.0276)	(0.0294)
W_COLLE	0.0508***	0.0410***	0.0399***	0.0648***	0.0475***	0.0460	0.108***
	(0.0151)	(0.0134)	(0.0116)	(0.0203)	(0.0152)	(0.0300)	(0.0232)
Constant	0.613	1.357	−0.858	1.095	0.660	−0.866	−7.665***
	(1.803)	(1.969)	(1.264)	(2.068)	(2.019)	(2.731)	(2.418)
lnalpha	0.262	0.212			0.346		
	(0.206)	(0.152)			(0.229)		
Observations	73	73	73	73	73	73	73
Pseudo R2	0.0662	0.0382	0.208	0.276	0.0747	0.185	0.293
ll	−197.6	−375.4	−105.8	−45.96	−196.1	−39.68	−60.30

Notes: STOCK_*XX* and W_STOCK_*XX* correspond, respectively, to stock of firms of the industry of each estimation and to spatially lagged stock of firms of the industry of each estimation.
Source: author's estimates, standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$