PAPER

Title: How do coworking spaces coagglomerate with service industries? The tale of three European cities

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Abstract:
In recent times, the emergence of coworking spaces (CSs) has changed the way the workers cooperate, but also how they carry out their activities. This phenomenon, limited mainly to urban areas, has spread heterogeneously in intra-urban space. The paper focuses on the location of CSs in Barcelona, Warsaw and Utrecht, three European cities that differ in terms of the typology of creation of these workspaces. In three analysed cities, CSs are mainly private initiatives, although in Barcelona they are mainly developed by small entrepreneurs, while in Warsaw - by large multinational CSs' companies. While using K-density (kd) functions and density maps, we contribute to the empirical literature by identifying how CSs coagglomerate with the service sectors, how CSs are concentrated in some core areas of each metropolitan area and how these factors differ between cities taking into account the typology of CSs.

Keywords: *coworking spaces, agglomeration, coagglomeration, Barcelona, Utrecht, Warsaw.*

JEL codes: R00, R39, Z00

1. Introduction

The emergence of coworking spaces (hereinafter CS) as places that provide creative, innovative, well-designed workplaces for independent workers – mainly freelancers or self-employed professionals – for a limited period of time (Mariotti et al., 2017), is not a new phenomenon in work organisation. The first CS was opened in 2005 in San Francisco and quickly new coworking spaces were opened across the globe. With over 250% increase of the count of the CSs and almost 400% increase of the number of CS users between 2015 and 2019 (2019 Coworking Forecast, 2019), the recent growth of the coworking sector has been surprisingly dynamic. The COVID-19 pandemic and consequent waves of lockdowns have reduced the scale of growth and led some CSs to limit or cease their operations, although CSs' flexibility still seems to be attractive to some users. It especially applies to suburban CSs functioning near the place of living of potential users (Mariotti and di Vita, 2021).

The growth of CSs has been triggered by the three following interrelated factors: (i) the sustaining important role of informal relationships between various knowledge, creative and digital workers (Moriset, 2014) based on trust and reciprocity, (ii) the drive towards urban regeneration, and (iii) broad changes in the nature of work (Montanari et al., 2020). From the other perspective, CSs operate because of the co-existence of various proximities (Micek, 2020) in a specific physical place. Organisational and social proximities in the form of non-hierarchical relationships constitute a CS. By providing the facilitative milieu (relational milieu; Gandini, 2015) for collaboration with the other users (Fuzi, 2014), CSs tend to abandon hierarchical relationships and gradually develop a specific atmosphere for socialization (Moriset, 2014). On top of that, CSs also provide business opportunities (Spinuzzi, 2012) and contribute to business performance by providing trust, community, learning and self-efficacy (Bouncken and Reuschl, 2018). We argue CSs facilitate doing business between their users and also with surrounding companies from the neighbourhood. Hence, it is important for CSs to provide a vibrant local environment full of creative and diversified businesses.

Mariotti (2015) distinguished four groups of location factors. The most traditional one includes localization and urbanisation economies. In the paper, we study both types of economies arguing there are positive externalities stemming from the agglomeration of CS and their coagglomeration with companies operating in different sectors that may cooperate. Lower transaction cost, large pool of talent and good access to other services is crucial for CSs as it enables face-to-face contacts and facilitates work of CSs' users. We follow the Coll-Martinez's and Mendez-Ortega's (2020, p. 5) view that 'it seems that the location of CS may be to some extent explained by the entrepreneurial environment in their surroundings.' Hence, one should expect to detect a coagglomeration of CSs with knowledge-intensive services, not only the co-agglomeration of CSs and creative industries as identified by Coll-Martinez and Mendez-Ortega (2020) in the case of Barcelona.

Some CS exert a significant influence upon urban economies and the surrounding urban milieu (Mariotti et al., 2017; Akhavan et al., 2021). First, by boosting the urban buzz (Capdevilla, 2015) through the concentration of highly skilled workers they help to develop creative cities (Moriset, 2014). Second, CSs contribute to urban regeneration (Mariotti et al., 2017; Akhavan et al., 2019) and to an emergence of start-ups in the service sector, too. Hence, service industries play a double role as the location factor of CSs and the consequence of their growth.

As an initially urban practice (Stam and van de Vrande, 2017; Merkel 2015, 2019), CSs tend to operate in large and medium-sized cities. Hence, the focus of the paper is on three cities (Barcelona, Utrecht, Warsaw) situated in various European countries, consequently representing various social and economic contexts.
In recent years we have gotten to know much more about the location patterns of CSs in European urban context (Mariotti et al., 2017; Bednar et al., 2021). However, what is missing in our understanding of CSs' development, is the thorough/overall detection of location factors on a larger sample of CSs. Until recently, few non-anecdotal studies have been made about the location determinants (see Mariotti et al., 2021). In the paper, we focus on one of the location determinants that is the co-presence of the other services nearby CS. We **aim to** compare the coagglomeration of CS and the other service industries (including knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS), in particular) representing different knowledge bases (symbolic, synthetic, analytical and mixed types).

By using three original databases the paper contributes to the ongoing research on spatial agglomerations of coworking spaces in at least four ways. First, despite the increasing importance of CS, their location patterns and coagglomeration with the other industries at the intra-urban level are relatively rarely studied. That is what our paper adds to a growing literature on the CS phenomenon. Second, there is also a scarcity of comparative cross-urban studies of CSs agglomeration and coagglomeration patterns. Such studies should help to compare spatial patterns and colocation of CSs and various industries between cities. Third, empirical studies often explain the coagglomeration of CSs and the creative industries (Lazzeretti et al., 2012; Boix et al., 2015; Lazzeretti et al., 2016; Inkinen and Kaakinen, 2016, Coll-Martínez and Méndez-Ortega, 2020). We argue there is a need to check potential coagglomerations of CSs with the different types of businesses representing varieties of knowledge intensities and knowledge bases. Then, we decided to widen the scope of analysis from the classical perspective of purely creative industries to all businesses. Fourth, it is one of few papers (Coll-Martínez and Méndez-Ortega, 2020) that applies distance-based measures (Kd function) to analyse the agglomeration of CS and their coagglomeration with the other service industries at the intra-urban level. The used method is not affected by the modifiable areal unit problem.

The paper is organized as follows. Section 2 reviews the theoretical and empirical literature on location, agglomeration and coagglomeration of CS, delivering a state-of-the-art in the field of intra-urban location of CSs and states our hypotheses. Section 3 presents the area of study, providing the economic context of development of CSs in the three cities studied. Section 4 describes the data and methodology used in the paper and Section 5 shows the empirical results. Finally, Section 6 presents our main concluding remarks.

2. Literature review

Agglomeration of CSs at intra-urban context

The literature review confirms CSs tend to agglomerate in three specific types of areas. First, CSs tend to spatially concentrate in the historical cores of cities or adjacent central business districts (Barcelona - Coll-Martinez and Mendez-Ortega, 2020; Milan and Prague - Bednar et al., 2021; Warsaw - Smętkowski et al.; 2019) that provide high density of various users, physical proximity to cultural amenities, and, on top of that, agglomeration of knowledge-intensive services (Coll-Martinez and Mendez-Ortega, 2020; Mariotti, 2015; Mariotti et al., 2017). City centers and business districts attract young workers (Berbegal-Mirabent, 2021). Second, CSs are situated in areas with good public transport accessibility, for instance close to the Central Station area (see the case of Milan; Bednar et al., 2021). Third, in a growing number of cases CSs choose low-priced abandoned and/or recently regenerated sites (see e.g. the case of Prague, Bednar et al., 2021), especially in the most advanced cities (Stam and van de Vrande, 2017). It also includes newly re-developed knowledge-intensive areas such as the 22@ district in Barcelona (Coll-Martinez and Mendez-Ortega, 2020). Moreover, location patterns may depend not only on the specific urban structure, but also on the ownership-based model of CSs' development (more independently run or corporate-owned; see Bouncken et al., 2018, Orel and Kubátová (2019). The location decisions of CSs change according to the type of provider (Coll-Martinez and Mendez-Ortega, 2020). They might be led by large global CSs providers (corporate-owned CSs), independent private individuals, or might be (semi-)public: run by a public institution (library; Bilandzic and Foth, 2013, di Marino et al. 2018) or a university (Bouncken, 2016). It applies, for instance to Warsaw, where corporate-owned CSs concentrate in two central business districts and independently run CSs are more dispersed within the city (Wojnar and Małochleb, 2022). Hence, in the paper we would like to check whether CSs agglomerate differently in cities with different CS development strategies (**RQ1**).

By sharing similar location determinants with knowledge-intensive services (Mariotti et al., 2017) location patterns of CSs resemble the spatial structures of KIS. Knowledge-intensive services tend to cluster spatially in CBDs, but often disperse to the most accessible sites across the city and even move to suburban centres (Garcia-Lopez and Muniz, 2010; Shearmur, 2012).

Co-agglomeration of CS with the other service industries and companies representing various knowledge bases

CSs concentrate in 'creative cities' of advanced economies (Moriset, 2014). The research of CS' location stems from the studies of spatial patterns of creative industries. CSs often collocate with the surrounding clusters of creative industries (Mariotti et al., 2017). Moreover, studies highlighted that CSs themselves attract creative industry firms (Akhavan et al., 2019; Mariotti and Pacchi, 2021). The newest papers (Mariotti et al., 2021) also emphasize the role of creative industries in attracting CS and vice versa. We believe that CSs benefit from the spatial proximity of miscellaneous firms offering services of various knowledge intensities. To grow, users of CSs require access to innovation that may be provided by knowledge intensive companies (Shearmur and Doloreux, 2019). However, the broader analysis of the economic profile of service companies coagglomerating with CSs is missing. Therefore, we would like to pose the following research question (**RQ2**): do CSs coagglomerate with different KIS/LKIS companies in analysed cities?

To identify varieties of service industries we use a knowledge base approach originally introduced by Laestadius (1998, 2007). It is an alternative approach to existing classification of industries according to product categories (NACE) or R&D-intensity (OECD). Knowledge base typology was further developed in the field of geography of innovation to grasp industry-specific differences (Asheim and Gertler, 2005) and finally expanded by Asheim (2007) to include the growing importance of creative industries. This typology classically comprises three types of knowledge base used as inputs into innovation: analytical, synthetic and symbolic (Asheim and Gertler, 2005; Martin and Moodysson, 2010; Asheim et al., 2011; Toedtling et al., 2011).

Analytical knowledge base is research-driven, strongly abstract and, to a large extent, theoretical, universal, and consequently codified (Asheim et al., 2017). It is often available worldwide and does induce global relations. **Synthetic** knowledge base is used in the case of application of specific technologies and has a strong tacit context (Aslesen and Freel, 2012; Asheim et al., 2017). Due to the tacit knowledge component industries relying on this knowledge base are more prone to agglomerate (Audretsch, 1998; Martin and Moodysson, 2010). **Symbolic** knowledge largely differs from the two mentioned-above types of knowledge bases. It relies on creating symbols, images, sounds and consequently 'meaning, desire, and aesthetic qualities' (Asheim et al., 2017). Its intangible and context specific products often require geographical proximity (Hauge and Hracs, 2010; Aslesen and Freel, 2012). This tripartite distinction is built on "ideal types", hence single industries are in real life composed of more than one knowledge base (combinatorial (mixed) knowledge bases; see Asheim et al., 2017). Moreover, combination of knowledge bases creates a facilitative milieu for radical innovations, emergence of start-ups, growth of existing companies, and new industrial path development (Asheim et al., 2017).

We argue CSs do not significantly require an analytical knowledge base as it is largely available worldwide. However, CSs seek for the other types of knowledge bases (combinatorial types, too) as the proper ground to introduce innovation. Therefore, we have posed the third research question: do CSs coagglomerate with companies representing synthetic, symbolic and combinatory knowledge bases? (**RQ3**)

3. Study area

We have selected cities that vary in terms of population (Table. 1) and functions and consequently occupy different positions within the urban hierarchies and ranks of global cities and. Warsaw (the capital city of Poland) is recognised as the alpha level city, whereas Barcelona as the alpha- level city (Loughborough University, 2018). Dutch Utrecht is classified much lower - as a sufficiency city, although it is one of the top European cities in terms of its economic competitiveness and well-developed R&D activities and high education sector. To sum up, the studied cities represent miscellaneous strategies of attracting CSs.

The selected cities represent various types of CSs' development model. With the vast majority of independently-run CSs Barcelona follows up the bottom-up strategy. Warsaw should be classified on the opposite pole (Smętkowski et al., 2019; Wojnar and Małochleb, 2022), as the majority of CSs is corporate-owned. Utrecht may be positioned between these two cases with a bit larger number of individually-run CSs.

Table 1. Comparative characteristics of analysed three cities

	Barcelona	**Utrecht**	**Warsaw**
Population (2020)	1,664,182	358,454	1,789,771
Area (km^2)	101.9	99.21	517.24
Population density (pop/km^2)	16,331	3,613	3,460
Number of firms (2020)	70,651	41,785	161,987
Number of CS	148	138	104
CS main development model	Bottom-up	Mixed (the majority bottom-up)	Top-down

Source: Own elaboration.

4. Data and Methodology

Data

The research data was acquired from different sources via the following procedure: first, from main web inventories of CSs specific for each country, second, each entry was checked by the query of CSs' personal websites, and Facebook sites. In the case of Warsaw the database was developed through analysis of major websites (coworker.com, spacing.pl, sharespace.work). Data about CS in Barcelona comes from *Creative Catalonia*, *Cowocat* and *Barcelona Navigator*, which are public agencies that collect data from CSs, as well as data from start-ups and creative firms in Catalonia. Our dataset for Barcelona contains 148 CSs in the city.Finally, data of CS in Utrecht comes from researchers at the University of Utrecht[1]. Finally, our dataset contains 104 CSs operating in Warsaw, 148 CSs - in Barcelona and 138 CSs - in Utrecht.

For all three cities we collected data about the CSs' location (latitude and longitude) in order to measure the agglomeration and coagglomeration of CSs with different types of KIS. The research is based on a comprehensive and up to date database including data collected just before (2019) and in the first phase of Covid-19 (spring 2020) pandemic.

Geospatial data for Barcelona-based companies come from SABI database, which provides information about more than 2 Million Spanish and Portuguese firms[2]. For Warsaw, data for the location of companies in Warsaw, Dun and Bradstreet data derived from EMIS (Emerging Markets Information Service) was used. In the case of Utrecht, data from Bureau van Dijk derived from the Amadeus database was used.

In the paper, we use the classification of services (and the distinction between KIS and LKIS) provided by Eurostat (XXX) Rev.2 and conduct analysis on the two-digit level of NACE Rev. 2 codes.

Table 2. Number of firms by city and typology

Acronym	**Name**	**Cities**		
		Barcelona (%)	**Warsaw (%)**	**Utrecht (%)**
KIS	Knowledge Intensive Sectors	23,815 (33.64)	64,968 (40.09)	28,932 (69.01)
LKIS	Less Knowledge Intensive Sectors	34,394 (48.57)	67,821 (41.85)	10,139 (24.18)
By type of Knowledge Intensive Sectors				
MKIS	Knowledge Intensive market services	11,836 (16.71)	32,666 (20.15)	11,232 (26.79)
FKIS	Knowledge Intensive financial services	3,083 (4.35)	7,559 (4.66)	239 (0.57)
HKIS	High-tech KIS	3,746 (5.29)	16,207 (10.00)	4,134 (9.86)
OKIS	Other KIS	5,150 (7.30)	8,536 (5.27)	13,327 (31.79)
By type of Activity				
ICT	Information and Communication activities	4,234 (5.59)	16,980 (10.48)	4,037 (9.63)

[1] Data about CS in the city of Utrecht was collected by Casper Leerssen, Veronique Schutjens, Joey O'Dell, Arne Eijgenraam, Boris Bleije, Floor Roll, Merlijne Hermans, Noa Eijgelshoven and Sterre de Rooij, members of a research group at the University of Utrecht, into the framework of the COST Action "CA18214 - The Geography of New Working Spaces and the Impact on the Periphery."

[2] SABI database include several firms' characteristics including year of entry, balance sheets, income, expenditure accounts, number of employees, industry, sales, assets, and georeferenced location (i.e., X-Y coordinates). SABI collects data from the Mercantile Register, where all limited liability companies and corporations are obliged by law to deposit their balance sheets. This is the most widely used dataset in Spain and Portugal when firm's georeferenciation is required and it is provided by Bureau Van Dijk.

STK	Professional, Scientific and technical activities	7,852 (11.09)	23,483 (14.49)	6,392 (15.25)
AER	Arts, Entertainment and recreational activities	1,336 (1.88)	1,661 (1.02)	4,745 (11.31)
	By type of Knowledge			
SYM	Symbolic Knowledge activities	3,770 (5.32)	8,158 (5.03)	6,888 (16.43)
SYN	Synthetic Knowledge activities	12,282 (17.35)	40,632 (25.03)	13,508 (32.22)
ANA	Analytical Knowledge activities	3,359 (4.74)	5,903 (3.64)	1,194 (2.85)
SYSY	Symbolic/Synthetic Knowledge activities	1,113 (1.57)	5,299 (3.27)	393 (0.94)
SYAN	Symbolic/Analytical Knowledge activities	3,291 (4.64)	4,976 (3.07)	6,949 (16.57)

Source: Own elaboration. Note: % in brackets.

To attribute the NACE classes to the different knowledge bases, we used previous classifications by Aselsen and Freel (2012) and Innocenti and Lazzaretti (2019) and transformed them using two-digit NACE classification. We argue that while studying complex and relatively wide industry classes a more nuanced approach should be used. Therefore, we widen the tripartite distinction by introducing mixed types of knowledge bases, namely synthetic/analytical and symbolic/synthetic (see Appendix 1). In our study, the majority of knowledge intensive service industries are classified under the synthetic or mixed (with synthetic) knowledge base that corresponds with the findings of Aslesen and Freel (2012).

Methodology

Firstly, heat maps showing the distribution of CS were made using a cluster map symbolization (heatmap) that presents point density as a continuous color gradient. This method allows for the calculation of point density based on the number of points in a given location, where the more points grouped together the higher the density values.[3] The data used for the study referred to the distribution of CSs in Barcelona, Utecht and Warsaw based on their geographical coordinates.

Secondly, K-density functions (Duranton and Overman 2005) give the density of firms using a distance-based approach in order to determine the distribution of bilateral distances between firms from the same activity and/or different activity. Let us define an industry S with n firms, then we compute a circle distance (i.e., radius) between each pair of firms in that industry, obtaining *n(n-1)/2* bilateral distances for industry *S*. We denote *d_ij* as the distance in meters between firms i and j. Finally, the K-density function at any distance d is defined as follows:

[3] For the representation of density maps, the constant method was used as a method of presenting symbols, which allowed comparing different areas at the same scale. The radius, which indicates at what distance from a point the impact of that point on a given area will be calculated, was given the value 10. The color scheme was chosen according to the type of phenomenon.

$$\widehat{K}(d) = \frac{1}{n(n-1)h}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} f(\frac{d-d_{ij}}{h})$$

, where h is the optimal bandwidth, and f is a Gaussian kernel function, where all densities are calculated. It's relevant to mention that an employment-weighted version of the K-density exists, but in this paper we are not using it because our research question, which focuses on the agglomeration and coagglomeration of the CS and different economic sectors in the cities of Barcelona, Warsaw and Utrecht considers exclusively the establishment's location and it is not necessary to assign a weight to each point.

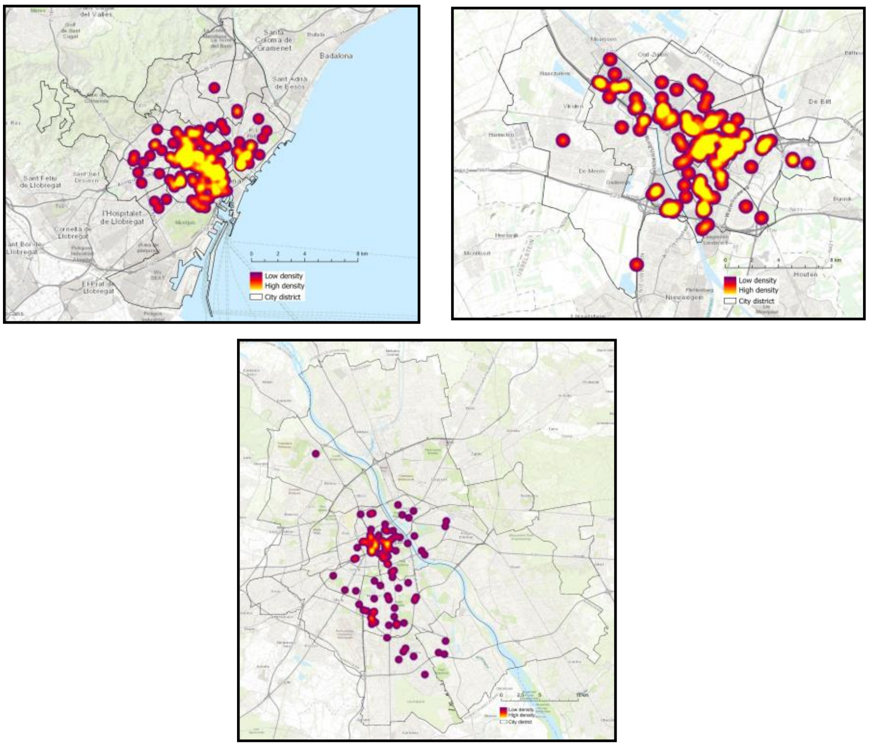
This function will be used at both intra- and inter-industry approaches, that would help to analyse the density of firms (bilateral firm distances) of an industry or the bilateral distance between a pair of industries comparing it with an average simulated value (whole economic activity) under the null hypothesis of same density value that the average simulated value for each distance. K-density. Function has been used in numerous papers in order to analyse the density of firms for each distance and how do firms agglomerate (i.e. Behrens et al., 2016 for the case of Canada or Méndez-Ortega and Arauzo-Carod, 2020, for the case of Barcelona, Lyon and Hamburg).

5. Results

Location patterns of CSs in the studied cities

With regard to the location of CSs, the highest density of CSs in Warsaw is observed in two business areas - the Central Business District (CBD) located in the city center and the Southern Business District (SBD) located in the west-south part. Within the city area there are numerous single CSs concentrated mainly in the central districts, with a lack of CSs on the outskirts of the city. Similar pattern of CSs' localization in the city center was observed in Barcelona. The city is characterized by several zones of high density of CSs, mainly in the south in Eixample, Gracia and Sant Marti districts (around the CBD of the city). As in the case of Warsaw, no CSs were observed near the city boundary. Utrecht has the most complex pattern of CSs' occurrence among all analysed cities, since CSs are located in every district with several outbreaks especially concentrated in the city centre and south and north of it.

Figure 1. Heatmap of location of CS by city.



Source: Own elaboration

To sum up, for Barcelona and Warsaw, CSs seek to be located in the CBD, an area with high firm's density, great variability and availability of amenities and well connected by public transport, being areas where rents are very high. This makes the CSs ideal spaces for firms with few resources, since they offer an optimal location at affordable prices. This firm's profile fits with KIS firms, since it is a type of firm which requires high-skilled human capital, amenities and good transport connection (Arauzo-Carod et al., 2017; Coll-Martínez and Méndez-Ortega, 2020).

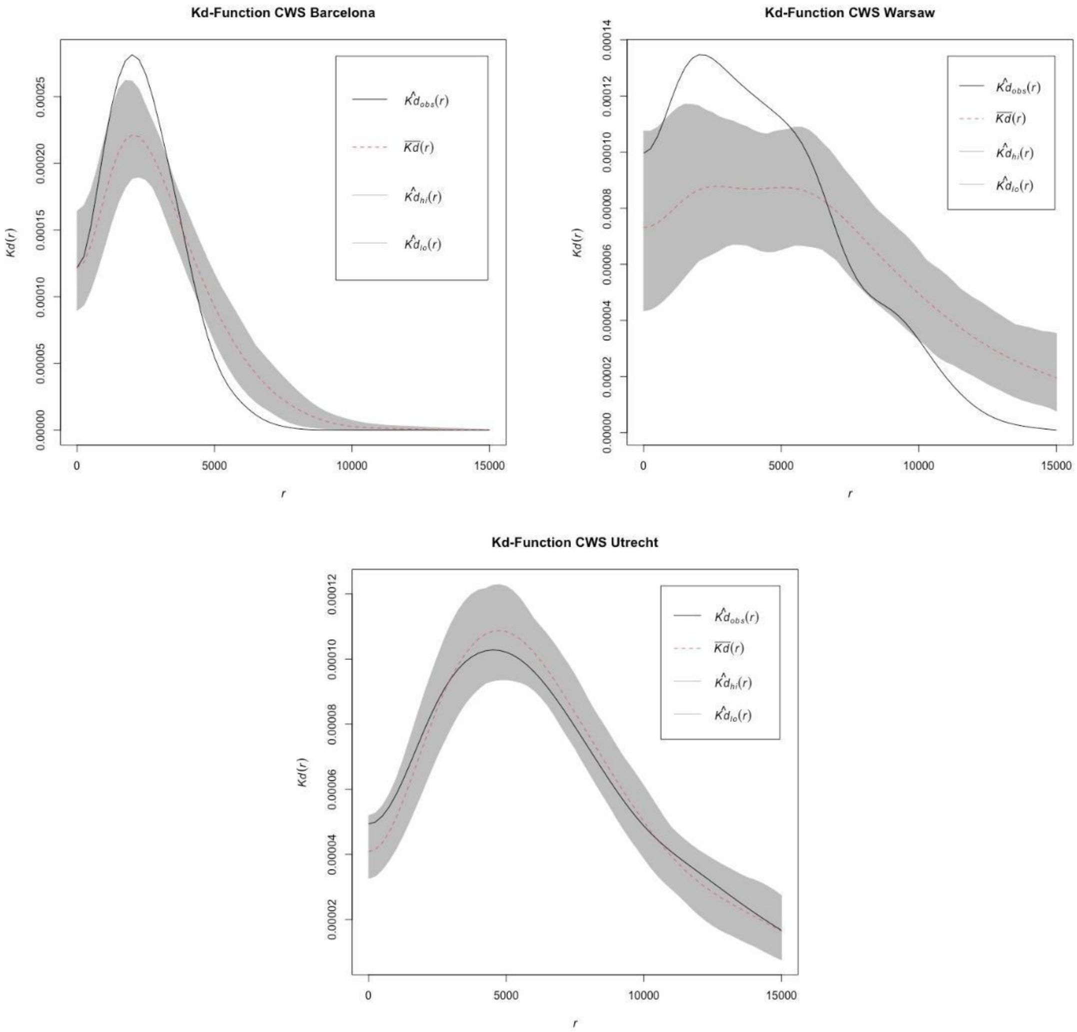
Agglomeration of CSs in the city

In this section we show the Kd function[4] of the CSs for the city of Barcelona, Warsaw and Utrecht. The results presenting the agglomeration of CSs in each city are shown in Figure 2. In the case of Barcelona and Warsaw, it reveals the agglomeration of CSs (for Barcelona significant between 1,200 and 3,000 meters (m), being the function peak at

[4] All calculations employ a 0.05 significance level, using 1,000 simulations. The dashed line corresponds to the benchmark scenario, that is a set of randomly drawn points, and the shaded area is the confidence interval (CI). The K-density function gives the density between points for each distance, in the case of agglomeration (i.e. when CSs' density is analyzed), kd values above CI indicates that at this distance, CSs are agglomerated and this agglomeration is statistically significant, values below CI reflect CSs dispersed, and this dispersion is statistically significant.

2,000 m with a Kd value of 0.000281, and for Warsaw from 750 and 5,250 m, with the peak at 2,000 m, too and Kd value of 0.000135). In the case of Utrecht, there is no statistically significant agglomeration, when we compare with the rest of firms in the city. Additionally, for the Dutch city Kd values are lower than for Barcelona and Warsaw.

Figure 2. Agglomeration of CS by city.



Source: Own elaboration. Note: Horizontal axis units (r) - meters.

The results for Barcelona and Warsaw could be explained by the huge concentration of CSs in the CBDs of these cities, since these spaces provide facilities such as easy access to public transport and a wide range of services and amenities, contributing to the emergence of environments that generate knowledge (Kim, 2018; Moriset, 2014). However, in the case of Utrecht, where it is not observed statistical significance in any section of the function, this can be explained by the high number of the KIS activities in the city (according to the used database, KIS firms represent almost 70% of the economic activity of the city, which increases to 93% if LKIS firms are included). As a consequence, the benchmark scenario is very similar to the one analysed, hence there is agglomeration, not statistically significant.

Coagglomeration of CSs in the city

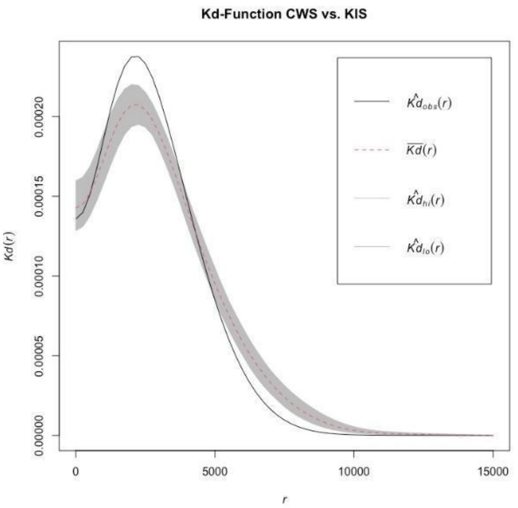
Once the agglomeration of CSs has been analysed for the cities, we proceed to analyse the coagglomeration of these spaces with different KIS and LKIS firms (1), general types of KIS (MKIS, HKIS, FKIS, OKIS) (2), specific types of KIS activities (ICT, STK, AER - representing large amount of creative industries) (3) and types of knowledge bases (4).

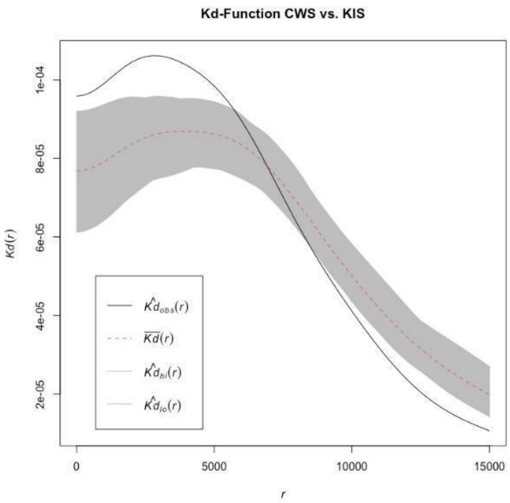
Coagglomeration of CSs with Knowledge Intensive Services (KIS) and Less Knowledge Intensive Services (LKIS)

On the one hand, compared with KIS, for Warsaw we found a coagglomeration statistically significant from 0 to 5,500 m, as for Barcelona (but just between 1,250 m and 3,250 m). The value of this density at the peak of 2,250 m is 0.000238 and in the case of Warsaw 0.000106 (at 2,750 m distance). Finally, for Utrecht the maximum is at 4,750 m (0.000105), but this is not statistically different from the density of all economic activities in the city.

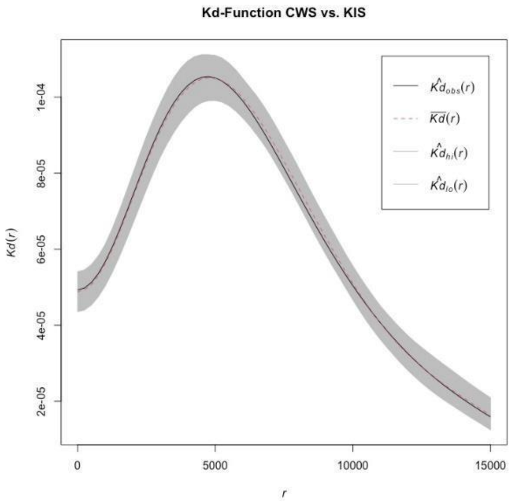
Figure 3. Coagglomeration of CS with Knowledge Intensive Sectors (KIS) by city.

Barcelona **Warsaw**





Utrecht

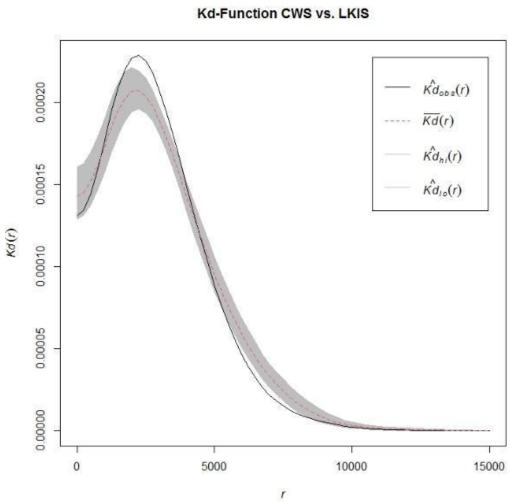


Source: Own elaboration. Note: Horizontal axis units (r) - meters.

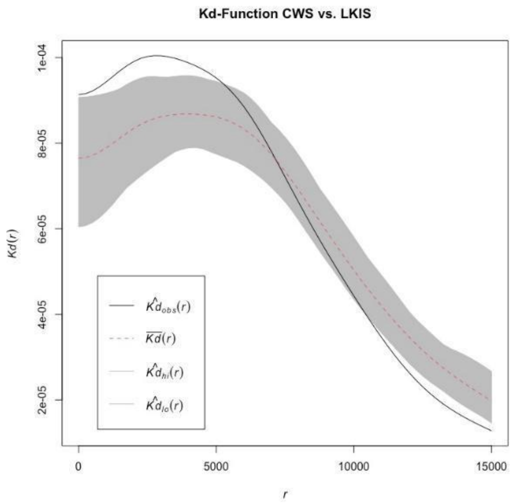
On the other hand, comparing with LKIS, for the case of Barcelona and Warsaw, both cities have Kd values lower than for KIS values, but yet they are statistically significantly higher than the rest of economic activity. For Utrecht, the coagglomeration is still not significantly different from the density of the economic activities. For Warsaw, the results show significance between 0 m and 5,250 m, with a peak of 0.0001 at 2,750 m. In the case of Barcelona, the significance is reported between 1,750 and 3,750 m, with a peak of 0.000229 at 2,250 m.

Figure 4. Coagglomeration of CS with Less Knowledge Intensive Sectors (LKIS) by city.

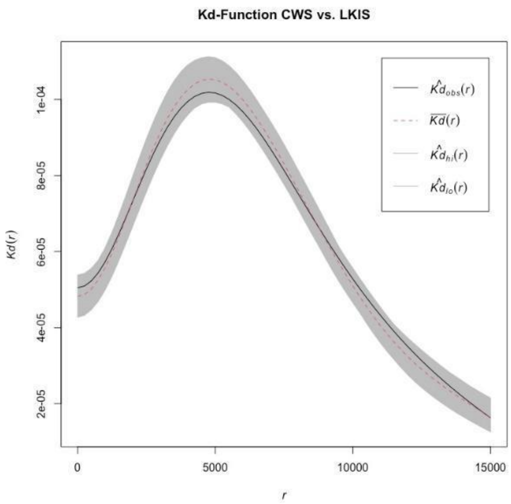
Barcelona



Warsaw



Utrecht



Source: Own elaboration. Note: Horizontal axis units (r) - meters.

In terms of the density value, the density of coagglomeration of KIS at the peak value in Barcelona is two times higher than the density in Warsaw (both significant) and Utrecht. Also, comparing densities between KIS and LKIS, even being significant in both cases, it is shown that the coagglomeration between CSs and KIS is higher than between CSs and LKIS.

These results show the importance of the spatial relationship between related activities such as CSs and KIS in the analysed cities due to the fact that KIS share the profile of worker that can be found in a CSs (Arauzo-Carod et al., 2017; Smętkowski et al., 2019).

Coagglomeration of CSs with general types of of knowledge intensive services: financial KIS (FKIS), market KIS (MKIS), high tech KIS (HKIS) and other KIS (OKIS)

Firstly, in the case of the coagglomeration of CSs with FKIS, for Barcelona and Warsaw we found statistical significance, higher than the density of economic activity. In the case of Warsaw, we revealed the significance from 0 m to 5,500 m, with a peak of 0.000114 at 2,250m (for Barcelona, from 1,250 m to 3,500 m, with a peak of 0.000238 at 2,000 m). For Utrecht, we found significant results on the first tram of the function (from 0 to 1,500 m, with a peak of 0.000068 at 1,500 m). There are only 239 FKIS firms in Utrecht that account for 0.57% share in the total number of the firms in the city - Table 2). It reveals that FKIS are highly clustered in a small area of the city of Utrecht. Secondly, in the analysis of CSs with HKIS, we found that the Utrecht case is not statistically different from the rest of economic activity across all the functions. For Barcelona and Warsaw we found coagglomeration of HKIS with CSs higher and statistically significant. In Barcelona these values are between 2,000 m where the peak value is 0.000269 and in Warsaw these values are from 0 m to 5,750m and the peak value is 0.000105 at 3,000 m.

Thirdly, for the case of MKIS coagglomeration with CS the situation resembles that for HKIS with statistical significance for Barcelona and Warsaw (in the same radius as for HKIS) and no statistical significance for Utrecht.

Table 3. Kd function values of CS by type of KIS.

	250m	500m	1000m	2000m	5000m	10000m
			Barcelona			
MKIS	0.0001467	0.0001585	0.0001951* *(CA)*	0.0002438* *(CA)*	7,92E+09* *(DS)*	4,05E+07
FKIS	0.0001338	0.0001464	0.0001852	0.0002380* *(CA)*	8,56E+09	4,53E+07
HKIS	0.0001294	0.0001416	0.0001799	0.0002369* *(CA)*	8,69E+09	3,18E+07
OKIS	0.0001122* *(DS)*	0.0001302* *(DS)*	0.0001719	0.0002354* *(CA)*	9,29E+09	2,31E+07
			Warsaw			
MKIS	9,82E+09* *(CA)*	9,89E+09* *(CA)*	0.0001013* *(CA)*	0.0001067* *(CA)*	9,83E+08* *(CA)*	3,99E+09* *(DS)*
FKIS	0.0001076* *(CA)*	0.0001085* *(CA)*	0.0001108* *(CA)*	0.0001144* *(CA)*	9,90E+09* *(CA)*	3,65E+09
HKIS	9,33E+09* *(CA)*	9,40E+09* *(CA)*	9,67E+09* *(CA)*	0.0001029* *(CA)*	0.0001002* *(CA)*	4,18E+09
OKIS	7,96E+09	8,05E+09	8,39E+09	9,27E+09	9,69E+09* *(CA)*	4,77E+09
			Utrecht			
MKIS	4,98E+09	5,13E+09	5,69E+09	7,44E+09	0.0001041	5,02E+09
FKIS	5,25E+09* *(CA)*	5,41E+09* *(CA)*	6,01E+08* *(CA)*	7,83E+09	0.0001054	4,72E+09
HKIS	4,84E+09	4,98E+09	5,52E+09	7,24E+08	0.0001030	5,16E+09
OKIS	4,86E+09	5,01E+09	5,58E+09	7,41E+09	0.0001072	5,01E+09

Source: Own elaboration. Note: m are meters, CA (Coagglomeration), DS (Dispersion), (*) - significance at 0.05 level.

Finally, for the coagglomeration of CSs with OKIS, we observed that for Barcelona there is a dispersion in the first tram (between 0 m and 500 m), indicating that the density of this sector with CSs in the first 500 meters is low. Then, for Warsaw and Utrecht there is no statistical significance in any radius.

Coagglomeration of CSs with specific types of KIS: Information and Communication activities (ICT), Professional, scientific and technical activities (STK) and arts, entertainment and recreation activities (AER)

For the case of Barcelona, it is important to highlight that there is coagglomeration between STK and CSs from 1,000 m to 2,000 m, showing a short linkage between scientific and technological activities and CSs in the city of Barcelona. For the case of AER, there is observed dispersion at the first 250 m, but coagglomeration at the 2,000 m, disclosing the existence of a polycentric pattern of these activities in the city of Barcelona. Finally, for ICT activities, we didn't find any relationship with CSs.

Table 4. Kd function values of CS by type of activity.

	250m	**500m**	**1000m**	**2000m**	**5000m**	**10000m**
			Barcelona			
ICT	0.0001324	0.0001449	0.0001838	0.0002405	8,39E+09* *(DS)*	2,87E+07
STK	0.0001487	0.0001607	0.0001977* *(CA)*	0.0002448* *(CA)*	7,85E+09* *(DS)*	4,43E+07
AER	0.0001181* *(DS)*	0.0001324	0.0001768	0.0002414* *(CA)*	8,77E+09	2,71E+07
			Warsaw			
ICT	9,23E+09	9,31E+09	9,57E+09* *(CA)*	0.0001019* *(CA)*	0.0001002* *(CA)*	4,21E+08* *(DS)*
STK	0.0001010* *(CA)*	0.0001017* *(CA)*	0.0001043* *(CA)*	0.0001094* *(CA)*	9,80E+08* *(CA)*	3,91E+09* *(DS)*
AER	9,12E+09	9,18E+09	9,39E+09* *(CA)*	9,86E+09* *(CA)*	9,53E+09* *(CA)*	4,48E+09
			Utrecht			
ICT	4,81E+09	4,95E+09	5,50E+08	7,24E+09	0.0001034	5,14E+09
STK	4,92E+09	5,06E+09	5,62E+09	7,35E+09	0.0001025	5,08E+09
AER	4,90E+09	5,03E+08	5,55E+09	7,21E+09	0.0001035	5,24E+09

Source: Own elaboration. Note: m are meters, CA (Coagglomeration), DS (Dispersion), (*) - significance at 0.05 level.

In Warsaw, as it is observed in Barcelona, there is a linkage between STK and CSs, being statistically significant from 0 m to more than 5,000 m. We also observe the same result for ICT and AER, but statistical significance starts at 1,000 m radius, revealing that the relationship between these activities and CSs in the city of Warsaw has a polycentric pattern. For the city of Utrecht none of these types of activities is statistically significant.

To sum up, in Barcelona and Warsaw we observe a strong spatial relationship between scientific and technological activities with CSs. Moreover, in the case of Warsaw, it

seems that there is a relationship of CSs with AER and ICT, due to the spatial polycentric distribution (Smętkowski et al., 2021) of these businesses in the city, since both activities are spatially linked to CSs at a certain radius. In Warsaw, creative advanced business services (that include AER and ICT) tend to be clustered in outer zones of CBDs (Smętkowski et al., 2021). A spatial relationship between CSs with AER and ICT is also observed in Barcelona, but just for arts and entertainment activities and at 2,000 m distance, due to the firm's distribution of these types of creative industries at the city and their strong linkages with the activities carried out in the CSs (Coll-Martínez et al., 2018).

Coagglomeration of CSs with different type of knowledge bases: Symbolic Knowledge activities (SYM), Synthetic Knowledge activities (SYN), Analytical activities (ANA), Symbolic-Synthetic Activities (SYSY) and Synthetic-Analytical Activities (SYAN)

Finally, we analysed the coagglomeration of CSs sorting by the type of knowledge base. We found heterogeneous results depending on the city and analysed type of knowledge base (Table 5).[5] In this case, three knowledge bases were splitted into five categories, to get more precise results.[6]

Table 5. Kd function values of CS by type of knowledge.

	250m	500m	1000m	2000m	5000m	10000m
			Barcelona			
SYM	0.0001302	0.0001447	0.0001890	0.0002496* *(CA)*	7,86E+09* *(DS)*	1,73E+07
SYN	0.0001339	0.0001451	0.0001804	0.0002338* *(CA)*	8,87E+09	3,96E+06
ANA	0.0001603* *(CA)*	0.0001740* *(CA)*	0.0002149* *(CA)*	0.0002564* *(CA)*	6,90E+09* *(DS)*	4,52E+07
SYSY	0.0001288	0.0001436	0.0001885	0.0002465* *(CA)*	8,27E+09* *(DS)*	3,21E+07
SYAN	0.0001265	0.0001387	0.0001773	0.0002349* *(CA)*	8,93E+09	3,80E+07
			Warsaw			
SYM	8,17E+09	8,27E+09	8,62E+09	9,57E+09* *(CA)*	0.0001015* *(CA)*	4,38E+09* *(DS)*
SYN	0.0001012* *(CA)*	0.0001018* *(CA)*	0.0001040* *(CA)*	0.0001084* *(CA)*	9,84E+09* *(CA)*	3,96E+09* *(DS)*
ANA	9,00E+09* *(CA)*	9,10E+09* *(CA)*	9,46E+09* *(CA)*	0.0001029* *(CA)*	9,80E+09* *(CA)*	4,19E+09* *(DS)*
SYSY	8,78E+09	8,87E+09	9,19E+09	9,96E+09* *(CA)*	0.0001003* *(CA)*	4,25E+09* *(DS)*
SYAN	8,59E+09	8,69E+09	9,06E+09	9,91E+09* *(CA)*	9,63E+09* *(CA)*	4,59E+09
			Utrecht			
SYM	5,23E+09	5,39E+09	6,00E+08	7,92E+09* *(CA)*	0.0001094	4,69E+09* *(DS)*
SYN	4,69E+09	4,83E+09	5,37E+09	7,10E+09	0.0001031	5,24E+09
ANA	4,78E+09	4,93E+09	5,46E+09	7,13E+09	0.0001003	5,19E+09
SYSY	4,65E+09	4,81E+09	5,40E+09	7,22E+09	0.0001019	5,04E+09
SYAN	4,94E+09	5,10E+09	5,69E+09	7,55E+09	0.0001074	4,92E+08

Source: Own elaboration. Note: m are meters, CA (Coagglomeration), DS (Dispersion), (*) - significance at 0.05 level.

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[5] Table A.1 of the annex shows the distribution of selected NACE codes for each type of knowledge.

[6] A similar analysis was done by Coll-Martínez and Méndez-Ortega (2020) for the city of Barcelona, revealing the coagglomeration of CS with specific knowledge bases. However, this analysis goes a step further, dividing three knowledge bases into five categories and comparing Barcelona with Warsaw and Utrecht, and providing a more wider and in-depth analysis.

Analyzing the results, in Barcelona, there is a strong coagglomeration of CSs with analytical knowledge base firms (ANA) that stretches between 0 m and 2,000 m. This phenomenon, for the case of Barcelona, is explained by the 22@ district, and area in the city that in recent years have attracted a several number of KIS firms, mainly with analytical knowledge base (Viladecans-Marsal and Arauzo-Carod, 2012 and Méndez-Ortega and Arauzo-Carod, 2019). Additionally, at 2,000 m radius, the rest of companies representing the other knowledge types is coagglomerated with CSs, due to the above-mentioned pattern of the city of Barcelona.

For Warsaw, we found coagglomeration statistically significant for all the knowledge types, although this coagglomeration is higher for firms representing synthetic and analytical knowledge bases (from 0 m to more than 5,000 m) and lower (but significant) for symbolic, synthetic-symbolic and synthetic-analytical ones (from 2,000 m to more than 5,000 m). These results show the importance of these activities and its connection with CSs in the capital of Poland and can be explained by the location strategy followed by the big corporations locating CSs in the city, establishing these shared spaces in areas with a huge density of companies that represent synthetic and analytical knowledge bases (Śleszyński, 2014, Smętkowski et al., 2021).

Finally, in the case of Utrecht we only found a slight (but significant) coagglomeration of CSs with companies representing symbolic knowledge base, but at 2,000 m radius, being a small density value. The limited coagglomeration observed in Utrecht, as it is mentioned above, could be explained by the regular spatial distribution of firms in the city.

6. Concluding Remarks

CSs are regarded as a new form of urban practice that generates urban buzz (Capdevilla, 2015), connects places (Merkel, 2015), but also forms spatial agglomerations (Bednar et al., 2021). In many cities representing different levels of urban hierarchy CSs tend to concentrate in a limited number of spatial clusters (Bednar et al., 2021). They are usually represented by central business districts and areas with good accessibility by public transport. It is exemplified in the case of two studied cities (Barcelona and Warsaw). However, in the third case (Utrecht) the results are interesting as the CS spread spatially in the city forming numerous micro-clusters, also in the former industrial areas and suburban locations. It might be explained by the high level of the city's competitiveness, its strong educational performance and dense land use. Hence, we confirm that CSs agglomerate differently in cities representing different levels of urban hierarchy and revealing different CS development strategies (**RQ1**).

CSs coagglomerate with different KIS companies in analysed cities (**RQ2**). It especially applies to Barcelona and Warsaw. For three studied cities CSs coagglomerate with KIS stronger than with LKIS (**RQ2**) as the vast majority of CSs' users work in the KIS sector and often provide or buy services to/from KIS companies. For Barcelona and Warsaw we found coagglomeration of high tech (including science and technology) and market KIS. Coagglomeration of CSs with the high-tech industries is explained by their connections. Firstly, Méndez-Ortega and Arauzo-Carod (2019) found that High-tech industries were spatially connected with Creative industries and, secondly, in Coll-Martínez and Méndez-Ortega (2020) found a connection between Creative industries and CS, these evidences are explained by the typology of work done at CS, being these activities connected with High-tech activities and, in consequence, high-tech firms and CS are spatially related. In the case of Warsaw, it seems that there is a spatial relationship of CSs with AER and ICT due to their location in outer zones of CBDs. In Utrecht, the coagglomeration of CSs with different types of KIS has been detected exclusively in the case of FKIS that tend to cluster spatially in a small area of the city.

Results on co-agglomeration of CSs and various types of knowledge bases are mixed (**RQ3**). CSs coagglomerate with firms representing symbolic knowledge base in Warsaw and Barcelona (at 2,000 m radius in Barcelona and larger distance for Warsaw). There is a weaker coagglomeration of CSs with synthetic knowledge firms (observed from 2,000 to over 5,000 m in Warsaw and at 2,000 m radius in Barcelona). Surprisingly, the strong coagglomeration on small distances up to 2,000 m is observed in this respect.

The paper holds some limitations. First, it must be kept in mind that we have treated CSs as black boxes, although they are built upon various freelancers, digital nomads and small firms that hold specific knowledge bases themselves. Second, the data on CS does not allow us to study the time dynamics on the location patterns of CS. It must be argued location patterns differ based on the stage of evolution of the CS sector in the given city. Third, district-level economic and social data should be included in an

exploratory analysis. Fourth, access to information about size and characteristics of CSs would help us to understand their location decisions.

We acknowledge there are many further research avenues for studying the location of CSs. During the COVID-19 pandemic trend towards location of CS in suburban areas, small towns and rural areas (COST report; Di Matteo and Mariotti 2020; Mariotti et al. 2021). Due to lower population density and congestion such areas attract coworkers and teleworkers as they provide a safer working environment than classical CS located in dense core cities. Moreover, CSs users prefer to work close to their own neighbourhood. When it comes to coagglomeration of CSs with the other industries the future research would benefit from linking directly the coagglomeration studies of coworking spaces with the other business activities using the related variety approach (e.g. co-location of CS with the creative economies) or the urbanisation economies (e.g. all services in total) (Caragliu, et al., 2016) as the explanatory frameworks.

With regard to policy implications, we argue that due to coagglomeration of CSs and high-tech services urban strategies that support technology and innovation should take into account the state-of the art and spatial distribution of CSs. That would help to establish the interaction between CSs users, technological and scientific professionals and creative workers.
Our results show also that while making a decision to start the coworking space, the spatial pattern of all service industries in a given city should be taken into account. For cities like Barcelona and Warsaw, the strategy of locating CS in the peripheral areas with low density of service industries may not be successful. For such cities the best step would be to stick to business districts. It is also shown by some CSs being shut down outside business districts in Warsaw during the Covid-19 pandemic (Wojnar and Małochleb, 2022).

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ANNEXES

Table A.1. Classification of firms by type using NACE.

NACE code	KIS	LKIS	MKIS	HKIS	FKIS	OKIS	ICT	STK	AER	SYM	SYN	ANA	SYAN	SYSY
45		X												
46		X												
47		X												
49		X												
50	X		X										X	
51	X		X										X	
52		X												
53		X												
55		X												
56		X												
58	X					X	X							X
59	X			X			X			X				
60	X			X			X			X				
61	X			X			X				X			
62	X			X			X				X			
63	X			X			X							X
64	X				X						X			
65	X				X						X			
66	X				X						X			
68		X												
69	X		X					X				X		
70	X		X					X			X			
71	X		X					X			X			
72	X			X				X				X		
73	X		X							X				
74	X		X										X	
75	X					X							X	
77		X												
78	X		X								X			
79		X												
80	X		X								X			
81		X												
82		X												
84	X					X							X	
85	X					X							X	
86	X					X					X			
87	X					X					X			
88	X					X					X			
90	X					X			X	X				
91	X					X			X	X				
92	X					X			X					X
93	X					X			X	X				
94		X												
95		X												
96		X												
97		X												
98		X												
99		X												

Source: Own elaboration.