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Predicting innovative growth and demand with proximate human capital: A case study of the Helsinki metropolitan area

Juho Kiuru [a,*], Tommi Inkinen [b]

[a] University of Helsinki, Department of Geosciences and Geography, Division of Urban Geography and Regional Studies, P.O. Box 64, (Gustaf Hällströmin katu 2a), FI-00014 University of Helsinki, Finland
[b] University of Turku, Centre for Maritime Studies, Brahea-Centre, FI-20014 University of Turku, Finland

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ABSTRACT

Human capital is an essential driver for the growth of national and regional innovation systems. In this study, we can show that also intra-metropolitan innovation clusters locate in, or in proximity to, neighbourhoods with a high level of human capital. Our interpretation of human capital involves an educated, talented, creative and tolerant workforce. Indicators from earlier literature are complemented by identified new propositions. In addition, by using both relative and absolute measures, we conclude that innovations emerge the best in dense and mixed urban structure. After identifying the geography of human capital and innovativeness, we predict also potential growth areas, which could help urban planning of the HMA. The modelling methods used in this study can be implemented and applied in urban studies of other city regions.

1. Introduction

Numerous studies have proven that one of the key drivers for economic growth is human capital. This refers to workforce characteristics, including indicators such as the level of education (tertiary), employment knowledge intensity, and employee know-how (e.g. Glaeser & Saiz, 2004; Alquézar Sabadie & Johansen, 2010). Other studies have applied the concept of creative class, including indicators of talent and tolerance of the workforce (Florida, 2002, 2012). Some studies have recognised the correlation between human capital and innovativeness in the national context (Barro, 1991; Rauch, 1993; Simon & Nardinelli, 1996; Simon, 1998). Similar approaches have also been used in regional and urban studies (Zucker, Darby, & Brewer, 1997; Glaeser, 2000; Henry & Pinch, 2000; Florida, 2002; Florida, Mellander, & Stolarick, 2008; Lawton Smith, 2009; Boschma & Fritch, 2009; Doms, Lewis, & Robb, 2010; Glaeser, Kerr, & Ponzetto, 2010). However, the connection between human capital (individual capabilities) and spatial innovation clusters (firm properties) has not been greatly studied on an intra-metropolitan scale.

Our study uses the Helsinki Metropolitan Area (HMA) that is the capital area and the most important economic concentration in Finland (Makkonen & Inkinen, 2015) as the case location. Finland has been deemed one of the most innovative countries in the world (e.g. World Economic Forum, 2015). This article presents a statistical analysis of the intra-regional characteristics and interdependencies within the HMA. It will also produce applicable research results for strategic planning. We will conduct a predictive analysis on the potential growth locations based on postal code data.

Our research questions are:

1) Do intra-metropolitan clusters of innovation locate in proximity to neighbourhoods with a high level of human capital?
2) How can we predict potential growth areas to help the urban planning of the area?

These research problems relate to both the international context and local urban planning. By discovering which indicators are relevant to intra-metropolitan innovation clusters, and which indicators of human capital predict local scale innovativeness, this study contributes to the international debate concerning innovation clustering, and especially to human capital driven growth.

The main findings of our study visualise and statistically verify that intra-metropolitan clustering of innovation and human capital hotspots are closely related, not only statistically but also spatially. Our study also provides indications of areas that could benefit from proximity to these innovation hotspots. Another main result is that our analysis illustrates (with solid, diverse, and independently collected datasets) degrees and volumes of distribution in terms of innovation and human capital indicators (spatial clustering presented in Fig. 1). In terms of practical suggestions, our spatial lag model results provide insights into new development actions, and bring forth new areas that could have

* Corresponding author.
E-mail addresses: juho.kiuru@helsinki.fi (J. Kiuru), tommi.inkinen@utu.fi (T. Inkinen).

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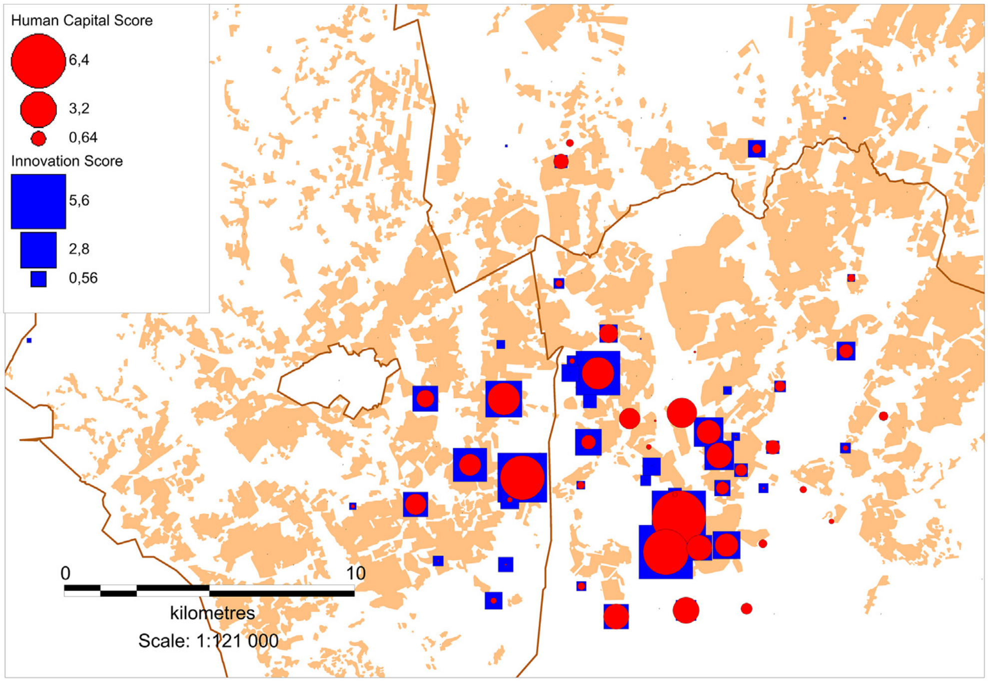

Fig. 1. Geographical distribution of human capital and innovation scores in the HMA.

potential for intra-urban strategic planning. The models used in this study can also be used and implemented in empirical urban research in other city regions that have similar data resources available.

2. Literature based background

Human capital has traditionally been considered important in the (innovative) economic growth of nations and regions, including the widely applied Porter's diamond approach (e.g. Barro, 1991; Rauch, 1993; Simon & Nardinelli, 1996; Simon, 1998; Porter, 2000) and regions (e.g. Zucker et al., 1997; Simon, 1998; Glaeser, 2000; Henry & Pinch, 2000; Florida, 2002; Simon & Nardinelli, 2002; Glaeser & Saiz, 2004; Florida et al., 2008; Lawton Smith, 2009; Boschma & Fritch, 2009; Doms et al., 2010; Glaeser et al., 2010; Florida, 2012). Fu (2007) demonstrated that human capital externalities work locally, even at the census block level in the Boston Metropolitan Area. In addition, the knowledge spill overs were evident only in the most central census blocks. Fu named the concept Smart Café Cities. However, in Fu's study, spillover effects were tested between workforce features. Our goal is to deepen the spatial focus of the relationship between human capital and innovation. This will also help to bridge the human capital and innovation clustering from regional studies towards urban studies.

Definitions of human capital have varied between an educated and skilled workforce (Glaeser 1994, Glaeser & Saiz, 2004; Alquézar Sabadie & Johansen, 2010) to talented and tolerant citizens (Florida, 2002). The tolerance aspect has received several criticisms (e.g. Clark, 2003; Glaeser, 2004) and has therefore been further redefined (Florida, 2012). The debate centres on whether firms locate in areas with an educated and skilled workforce (Florida, 2002, 2012), or whether employees follow the firms (e.g. Scott, 2000, 2006). Earlier studies have also recognised that human capital observed from surrounding areas is more influential concerning innovation clustering than the area itself (Simonen & McCann, 2008). Therefore, the spatial interdependence between human capital and innovative output is also tested. This enables us to answer the question of whether the human capital of a neighbouring area influences the innovative capacity of small observation units, such as postal codes.

Considering single variables, tertiary education is one of the most important indicators associated with the human capital concept. Education has been widely studied in urban and regional studies, and it is deemed to be one of the most important societal indicators depicting potential and actualised levels of innovation at a location (e.g. Doms et al., 2010; Glaeser et al., 2010; Makkonen & Inkinen, 2013). Additionally, the workforce age structure is significant. This refers to the number of skilled workers in the age groups close to 40 years (e.g. Bönte, Falck, & Heblich, 2009; Glaeser & Kerr, 2009). Other recognised measures include the number of creative occupations (e.g. Florida, 2002; Marlet & Van Woerkens, 2004; Mellander & Florida, 2006; Boschma & Fritch, 2009; Florida, 2012) and the proportion of skilled professional immigrant workforce (Stephan & Levin, 2001; Florida, 2002). In this study, we will measure creative occupations with the Standard Industrial Classification (SIC).

From single indicators, inadequate figures for artists, immigrants and gay people have been criticised in several studies (e.g. Clark, 2003; Glaeser, 2004). In this study, different indicators of human capital, including the aspect of tolerance, are tested. Instead of the number of immigrants, we measure areal tolerance, using the popularity of immigration-critical political parties as a gauge. We believe that a low popularity of immigration-critical political parties sufficiently reflects the tolerance of different areas. We bring a new indicator of workforce tolerance into the analysis of human capital. Another feature of this study is that the density of human capital is included in the analysis, by measuring the number of both relative and absolute indicators. The study demonstrates that the relationship between tolerance and innovation or human capital measures only holds for highly populated areas on the postal code level (Clark, 2003). Bringing together the balance between share and volume, i.e. the relative and absolute level of human capital, is also a new view point to studies concerning HMA. These have usually examined proportions, and therefore have concluded that detached housing areas with a high share (relative) of professionals are more important than more densely populated areas hosting a higher absolute number of these professionals for innovation driven development and economic growth (e.g. Vaattovaara, 1998; Vilkama, Lönnqvist, Väliniemi-Laurson, & Tuominen, 2014; Kiuru, 2015).

We recognise the difficulty of measuring the different ways of innovativeness, creativity and skill or know-how. Patents are probably the most commonly used indicator (e.g. Carlino, Chatterjee, & Hunt, 2007;

Kerr & Kominers, 2010; Carlino, Carr, Hunt, & Smith, 2012; Murata, Nakajima, Okamoto, & Tamura, 2012), but patents have also faced criticism since they quantify mainly technical innovations, far too often excluding social innovations, for example. In addition, several patents never reach the market and their importance is therefore questionable. R&D activity is another way of examining a region's innovativeness (e.g. Audretsch & Feldman, 1996; Kenney, 2000; Agrawal, Cockburn, & Rosell, 2010; Lee & Nicholas, 2012), but R&D projects do not necessarily turn into innovations, however. R&D expenditure is also an innovation input and that tells nothing about the outputs to or impacts on markets. One way is to examine the amount of knowledge intensive business service (KIBS) firms (e.g. Manniche, 2012; Inkinen & Kaakinen, 2016). In addition, in the few decades since the work of Jacobs (1969), urban density has again been raised as an essential factor for innovative and economic growth (e.g. Fritsch, 2004; Boschma & Fritch, 2009; Malizia & Motoyamab, 2015). Therefore, we will examine both the absolute and relative innovativeness of postal code areas.

One interesting aspect of earlier innovation studies is the discovery of innovation paradoxes. Rodriguez-Pose (1999) discovered that some regions exhibit stronger (innovation averse) and some regions exhibit weaker (innovation prone) than expected economic growth relative to their R&D activity (see also Makkonen & Inkinen, 2013). The same concept could be implemented in measuring the region's innovative growth regarding their human capital.

From these starting points, we examine the spatial relationship between an educated, skilled and tolerant workforce (human capital), and innovative output in intra-metropolitan clusters. As the causation between human capital and innovations would need longitudinal data, which we do not have, we are unable to say which came first: human capital (Florida, 2002) or innovations (Scott, 2000, 2006). This is mainly because the standard industrial classification in Finland changed in 2008, making the comparison between the years before and after that date very problematic, if not impossible. An educated, skilled and tolerant workforce may generate innovation, but also knowledge-intensive firms and their establishments may attract professionals. In this respect, the last research problem was to identify clusters that underperform regarding the level of nearby human capital, and clusters that are more innovative than expected regarding the proximity of human capital. We predict potential clusters of innovations, as well as include the future demand for increasing the number of professionals. Findings of underperforming spatial areas can be implemented initially in HMA strategic planning. These areas could benefit, for example, from commercial zoning, new master plans and actions from business services departments. On the other hand, overachieving areas could benefit from new residential development motivated by the increased demand of the new professionals.

3. Data and methods

First, we collected potential indicators used to measure innovativeness in earlier literature (see upper part of the Table 1). After identifying the most significant input and output innovation indicators, we also considered the absolute and relative measures depicting innovation. After collecting statistical data, we obtained the number of KIBS establishments (a point pattern GIS data) from the Helsinki Region Environmental Services Authority (HSY). Data is freely available for research purposes. We included only private sector firms in our analysis, following the classification defined by Inkinen and Kaakinen (2016) in their earlier study. There are three occupational classes: Class I includes the ICT sector establishments, Class II consists of R&D and education workplaces, and Class III is formed from business services jobs. A fourth variable combines each subcategory into a sum variable (total number of class I-III establishments).

In the second phase, we collected potential indicators for measuring human capital (see the bottom part of Table 1). These include, for example, the number and share of tertiary degrees; the number and share of professionals working in knowledge-intensive fields (e.g. R&D, education, ICT); the number and share of artists; and the absolute and relative popularity of immigration-critical parties. This last point needs some additional explanation: both absolute and relative votes were taken into consideration for the following parties in the 2011 parliamentary election: True Finns, the Independence Party, and Change 2011, all of which had immigration criticism on their agenda).

The variables presented in Table 1 were treated as follows: R&D activity was measured with data from Tekes (The Finnish Funding Agency for Innovation). The data consisted of rows of granted R&D projects with information on the postal code area of the applicant and the amount of funding (in Euros) that was granted. We combined these attributes with GIS data on postal code areas (from HSY) to conduct a spatial analysis. Tekes is only one of the funding sources for R&D development, but we hypothesised that the funding from the most important single innovation agency sufficiently indicated broader R&D activity. In our analysis, we included the number of grants for the private sector, as well as the total sum of money for the private sector. The data concerning patents was obtained from the Finnish Patent and Register Office, and only patents that had been applied for by the private sector were included. Thus, commercial innovation clustering could be examined. We converted the raw data into GIS data, as was done with the R&D projects.

Information concerning tertiary degrees, students and residents aged 35–44 are all open data in the Statistics Finland website (database Paavo). The information is available at the postal code level, enabling us to examine the intra-metropolitan spatial distribution. The education data was combined with the GIS data, as was the case with the innovation data. Information on elections is classified with respect to election areas, which are slightly different from postal code areas. This problem was solved by using the "proportion sum" operation in MapInfo software, which placed the number of election area votes to postal codes regarding the proportion of spatial overlapping. Other human capital variables were obtained from the Finnish Environment Institute (YKR). This is the only data that has a chargeable license. The data consists of 250 m cells, which have multiple attributes related mainly to the urban and social structure. We aggregated the cell data into postal code areas with respect to the proportion of each cell overlapping the postal code area. The latest data of some of the indicators are from 2012, so we used that year in our other variables as well.

After the data was collected, we applied Principal Component Analysis (PCA) to innovation indicators with IBM SPSS Statistics software. By doing that, we could find out which of the indicators were significant for measuring innovativeness. With PCA scores of the most potent component we identified innovation clusters in the HMA with one measure. Clusters were determined simply by classifying postal code areas into three categories regarding their PCA scores.

After establishing the innovation score, we tested all the potential human capital variables using OLS regression analysis (the only option of statistical regression in GeoDa software). Because there was a relatively large number of variables (16, Table 1) compared to the sample size (179 postal code areas), the variables were split into two groups of predictive components. The logical division was to separate the groups into absolute variables and relative indicators. The constant variable was the PCA score of the innovation indicators.

The literature concerning innovative capacity includes a conclusion that human capital from other regions has more influence on innovation clustering than the human capital of the area itself (Simonen & McCann, 2008). Therefore, the spatial correlation between human capital and innovativeness was tested using also spatial regression analysis. Thus, we analysed whether or not the human capital of neighbour areas influenced the innovative capacity. Similarly, in the field of urban geography, Song (2014) has used spatial regression in the analysis of land cover in Beijing. Similarly, Chi (2011) predicted

Table 1
Innovation and human capital indicators with descriptive statistics.

Variables for innovation	Source	Availability	Min	Max	Median	Average	St. dev.
the absolute number of area's private sector knowledge intensive jobs (inputs)	Helsinki Region Environmental Services Authority (HSY)	Free when asked	0	9486	89	524	1256
the relative share of area's private sector knowledge intensive jobs of area's total jobs (inputs)	Helsinki Region Environmental Services Authority (HSY)	Free when asked	0	73	12	16	13
the absolute number of area's private sector patents (outputs)	Finnish Patent and Register Office	Free when asked	0	66	0	2	8
the relative share of area's private sector patents of area's total jobs (outputs)	Finnish Patent and Register Office	Free when asked	0	0.04	0	0.001	0.004
the absolute number of area's private sector R&D projects	The Finnish Funding Agency for Innovation (Tekes)	Free when asked	0	69	0	0.3	8
the relative share of area's private sector R&D projects of area's total jobs (inputs)	The Finnish Funding Agency for Innovation (Tekes)	Free when asked	0	0.02	0	0.001	0.002
the absolute number (euros) of area's R&D spending (inputs)	The Finnish Funding Agency for Innovation (Tekes)	Free when asked	0	15,339,350	0	746,867	2,123,592
the relative share of area's R&D spending of area's total jobs (inputs)	The Finnish Funding Agency for Innovation (Tekes)	Free when asked	0	2676	0	200	456

Variables for human capital	Source	Availability	Min	Max	Median	Average	St. dev
The absolute number of area's tertiary degrees	Statistics Finland (Database "Paavo")	Open data	0	4929	636	854	762
The relative number of tertiary degrees of area's total workforce	Statistics Finland (Database "Paavo")	Open data	0	40	17	18	10
The absolute number of area's students	Statistics Finland (Database "Paavo")	Open data	0	2169	400	463	363
The relative number of students of area's total workforce	Statistics Finland (Database "Paavo")	Open data	0	37	7	8	4
The absolute number of 35–44-year-old residents	Statistics Finland (Database "Paavo")	Open data	0	3085	727	843	645
The relative number of 35–44-year-old residents of area's total residents	Statistics Finland (Database "Paavo")	Open data	0	21	14	14	4
The absolute number of professionals working in R&D	Finnish Environment Institute (Database "YKR")	Paid	0	6545	62	294	718
The relative number of professionals working in R&D of area's total workforce	Finnish Environment Institute (Database "YKR")	Paid	0	48	6	8	7
The absolute number of professionals working in the fields of the ICT industry	Finnish Environment Institute (Database "YKR")	Paid	0	4915	20	268	758
The relative number of professionals working in the fields of the ICT industry of area's total workforce	Finnish Environment Institute (Database "YKR")	Paid	0	52	2	5	8
The absolute number of professionals working in finance and insurance	Finnish Environment Institute (Database "YKR")	Paid	0	4546	3	130	495
The relative number of professionals working in finance and insurance of area's total workforce	Finnish Environment Institute (Database "YKR")	Paid	0	30	0.4	2	4
The absolute number of artists	Finnish Environment Institute (Database "YKR")	Paid	0	1760	20	82	183
The relative number of artists of area's total workforce	Finnish Environment Institute (Database "YKR")	Paid	0	17	2	3	3
The absolute number of votes for immigration-critical parties	Finnish Environment Institute (Database "YKR")	Paid	0.002	2992	375	532	506
The relative number of votes for immigration-critical parties of area's total votes	Finnish Environment Institute (Database "YKR")	Paid	4.59	31	16	16	6

population growth in the census tracts of Milwaukee using spatial regression, and Duncan (2013) used the method to assess the connection between urban form and depression.

Similarly, in spatial lag regression analysis, the constant variable was the PCA score of the innovation indicators. The predictors were absolute indicators from Table 1 in the first analysis and relative indicators from Table 1 in the second analysis. After two OLS analyses and two spatial lag analyses, a final OLS and spatial lag analyses (all six models in Table 3) were made of all the significant variables from the first four analyses. This allowed us to measure human capital and predicted growth with the combined model using both level and proportional variables.

With the predicted innovation values of the final analysis, we identified the clusters of human capital in the HMA. We classified postal code areas into three classes and presented them on two thematic maps (Figs. 1 and 2). Further, using spatial regression, we revealed the correlation between nearby human capital and innovativeness, and predicted the areas that could potentially be more innovative. We used residual values, i.e. the gap between true and predicted innovative output, of the final spatial lag analysis. Conversely, with negative residual values, we predicted the areas that could potentially attract more professionals. We performed the analysis using GeoDa open source software. We illustrated the analyses with MapInfo software.

4. Results

4.1. Principal component analysis, OLS and spatial lag models

The first component of the PCA analysis had an explanation level of 42% compared to 14% of the second component (Table 2). The first component was dominated by absolute indicators, whereas the second component consisted of relative indicators. We used the PCA score of the first component in further analysis. The relative number of patents and relative number of R&D establishments were the only ones that were not significant in the first component, and therefore were left out from the innovativeness score.

After finding out the innovation score, we tested all the potential human capital variables by using OLS regression analysis. Looking at the F-Statistic value, it is apparent that both tests reached the maximum statistical significance (<0.001) values, respectively (Table 3, models 1 & 2). R-squared values indicate that the variables chosen to explain the innovative output were highly effective, as the group of absolute indicators explains 85% of the dependent variable and the group of proportional variables explains 44%. This result means that the indicators may be used in studies of other city regions as well.

Further analysis of the results of the regression analysis, revealed that independent variables were not highly correlated (the multicollinearity

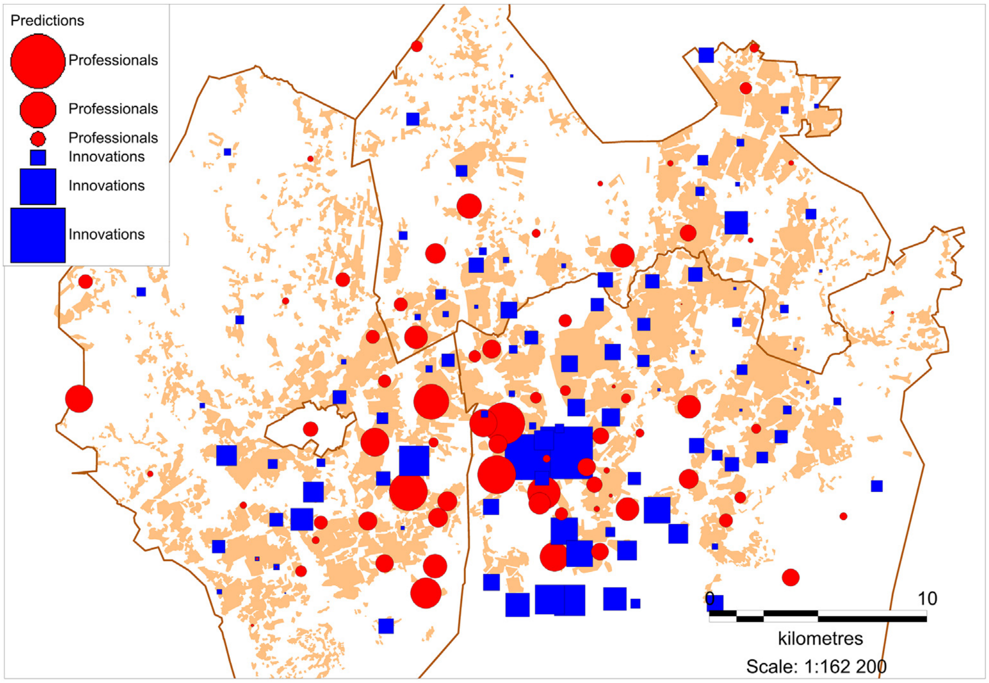

Fig. 2. Predicted geography of innovation prone and future demand areas in the HMA.

value is 14 in an absolute dataset and 20 in a relative dataset). The next step was to find out whether there was a spatial dependence, i.e. that the values of the nearest neighbours were significant, between predictors and constant variables. Regarding spatial dependence, it is apparent that both lag and error Lagrange Multiplier (LM) values were significant in both datasets. Robust LM suggests that there was only a spatially lagged dependence in both datasets. Therefore, a spatial lag analysis was conducted for both absolute and relative variables.

From the spatial lag analysis, we observed that consideration of the level of human capital of the neighbouring areas (in addition to the area itself) added analytical value. The neighbourhood effect was evident: the absolute level of human capital prediction was 88% of the innovative capacity of an area and its neighbours, compared to 85% if the predicted area was considered alone. In the case of relative human capital, the corresponding number rose from 44% to 49% when neighbouring areas were considered. Adding the second order of contiguity (the neighbours' neighbour) gave no additional value to our predictions. In fact, the model explained only 85% of innovativeness with the absolute variables. The model with proportional variables functioned in the same way: explanation was lower with a contiguity of two (45%) compared to a contiguity of one (49%).

In the case of individual indicators (Table 1), the only variable that did not predict the innovative output of locations, in neither absolute nor relative terms, was the resident's age when approaching 40. All the other indicators had significance at least in one of the four examined models (Table 3, models 1, 2, 3 & 4). To measure total human capital and predicted growth with combined level and proportional variables, we conducted a final analysis (Table 3, models 5 & 6), using only significant variables from the first four regression analyses. We interpreted that scores of the first component of the PCA represented innovativeness. Predicted innovation scores of the final OLS analysis represented the elemental variables from the human capital indicator set (see Table 1). Further, we predicted areas defined as having innovation potential, and areas with future demand for skilled professionals with residual

Table 2
Principal component analysis results for original data ($N = 179$).

Extraction method: Principal component analysis. 4 components extracted	Component			
	1	2	3	4
Absolute number (PCS.) of R&D projects	**0.902**	−0.237	0.062	−0.194
Absolute money (euros) spent on R&D	**0.879**	−0.215	0.092	−0.230
Absolute number of patents	**0.499**	−0.120	0.297	0.481
Relative number (PCS.) of R&D projects (compared to number of KIBS establishments)	0.349	**0.704**	0.368	−0.326
Relative money (EUROS) spent on R&D (compared to number of KIBS establishments)	0.381	**0.609**	0.287	−0.419
Relative number of patents (compared to number of KIBS establishments)	0.069	0.050	0.359	0.707
Absolute number of it establishments	**0.865**	−0.240	−0.016	0.015
Absolute number of R&D establishments	**0.597**	0.007	−0.609	0.024
Absolute number of business services establishments	**0.844**	−0.297	−0.033	−0.079
Absolute number of KIBS establishments altogether	**0.942**	−0.281	−0.082	−0.035
Relative number of it establishments (compared to number of establishments)	**0.682**	0.101	0.151	0.193
Relative number of R&D establishments (compared to number of establishments)	0.108	**0.473**	−0.759	0.138
Relative number of business services establishments (compared to number of establishments)	0.418	**0.477**	0.206	0.229
Relative number of KIBS establishments altogether (compared to number of establishments)	0.623	**0.612**	−0.277	0.306
Eigen value	5.86	2.037	1.54	1.311
% of variance	42%	14%	11%	9%

Table 3
OLS-models (1, 2 and 5) for absolute, relative and combined variables; and corresponding spatial lag models (3, 4 and 6). Dependent variable in all models is the innovation score.

Dependent variable: Innovation Score	Model 1 (OLS_absolute)	Model 2 (OLS_relative)	Model 3 (SpaLag_absolute)	Model 4 (SpaLag_relative)	Model 5 (OLS_combined)	Model 6 (SpaLag_combined)
Constant	−0.385	−0.279	0.348	−0.431	−0.165	−0.226
t-stat or z-value (sig)	−7.298 (***)	−0.738	−7.554 (***)	−1.213	−1.029	−1.526
Independent variables						
Lagged innovation score	Excluded	Excluded	0.292	0.294	Excluded	0.237
z-value (sig)			6.624 (***)	3.323 (***)		4.800 (***)
Students_abs	−2.320e-005	Excluded	3.185e-005	Excluded	Excluded	Excluded
t-stat or z-value (sig)	−0.118		0.185			
Immigrant_abs	−2.581e-005	Excluded	1.682e-005	Excluded	Excluded	Excluded
t-stat or z-value (sig)	−0.316		0.236			
Age_abs	1.891e-005	Excluded	−1.074e-005	Excluded	Excluded	Excluded
t-stat or z-value (sig)	−1.369		−0.899			
Tertiary_abs	2.941e-005	Excluded	1.308e-005	Excluded	6.229e-005	3.903e-005
t-stat or z-value (sig)	3.741 (***)		1.818		1.281	0.879
IT_abs	5.720e-005	Excluded	5.579e-005	Excluded	4.411e-005	4.862e-005
t-stat or z-value (sig)	9.124 (***)		10.242 (***)		5.694261 (***)	6.817 (***)
Finance_abs	−1.275e-005	Excluded	3.646e-006	Excluded	N/A	N/A
t-stat or z-value (sig)	−0.140		0.046			
R_D_abs	8.394e-005	Excluded	7.942e-005	Excluded	8.525e-005	8.264e-005
t-stat or z-value (sig)	10.738 (***)		11.552 (***)		10.436 (***)	11.023 (***)
Arts_abs	−11.652e-005	Excluded	−12.369e-005	Excluded	−9.852e-005	−11.611e-005
t-stat or z-value (sig)	−4.201 (***)		−5.127 (***)		−3.850 (***)	−4.930 (***)
Students_prop	Excluded	0.039	Excluded	0.036	−0.001	−0.005
t-stat or z-value (sig)		2.43 (*)		2.371	−0.135	−0.696
Immigrant_prop	Excluded	−0.041	Excluded	−0.024	−0.019	−0.009
t-stat or z-value (sig)		−2.692 (**)		−1.593	−3.174 (**)	−1.427
Age_prop	Excluded	0.029	Excluded	0.027	Excluded	Excluded
t-stat or z-value (sig)		1.468		1.427		
Tertiary_prop	Excluded	−0.013	Excluded	−0.013	Excluded	Excluded
t-stat or z-value (sig)		−1.271		−1.328		
IT_prop	Excluded	0.051	Excluded	0.046	0.012	0.007
t-stat or z-value (sig)		6.070 (***)		5.828 (***)	2.195 (*)	1.273
Finance_prop	Excluded	0.042	Excluded	0.036	0.011	0.008
t-stat or z-value (sig)		2.931 (**)		2.680 (**)	1.465	1.136
R_D_prop	Excluded	0.029	Excluded	0.024	0.006	0.004
t-stat or z-value (sig)		2.901 (**)		2.633 (**)	1.268	0.824
Arts_prop	Excluded	−0.027	Excluded	−0.028	Excluded	Excluded
t-stat or z-value (sig)		−1.569		−1.731		
Model summaries						
Number of cases (N)	179	179	179	179	179	179
Number of variables	9	9	10	10	10	11
Degrees of freedom	170	170	169	169	169	168
R-squared	0.847	0.444	0.878	0.486	0.866	0.883
Adjusted R-squared	0.840	0.418	N/A	N/A	0.859	N/A
Sum squared residual	26.544	96.218	N/A	N/A	23.164	N/A
Sigma-square	0.156	0.566	0.118	0.497	0.137	0.1136
S.E. of regression	0.395	0.752	0.343	0.705	0.370	0.3370
F-statistic	117.348	16.985	N/A	N/A	121.567	N/A
Prob (F-statistic)	0.000 (***)	0.000 (***)	N/A	N/A	0.000 (***)	N/A
Log likelihood	−83.171	−198.431	−63.961	−192.950	−70.981	−60.256
Akaike info criterion	184.342	414.862	147.921	405.900	161.962	142.511
Schwarz criterion	213.029	443.549	179.795	437.774	193.835	177.572

* = sig. <0.05
** = sig. <0.01
*** = sig. <0.001

values from the final spatial lag analysis. All in all, there were five human capital indicators that predicted postal code level innovativeness in our final model combined OLS model 5 (Table 3):

$IS = 0.441 * IT\_abs + 0.853 * R\_D\_abs - 19.264 * Immigrant\_prop + 12.025 * IT\_prop - 0.985 * Arts\_abs$

The dependent variable (IS) is the calculated innovation score (*1000) and the explanatory variables are: IT_abs = The absolute number of ICT professionals (t-statistic: 5.69; sig. 0.000; $N = 179$); R_D_abs = the absolute number of R&D professionals (t-statistic: 10.43; sig. 0.000; $N = 179$); Immigrant_prop = the relative popularity of immigration criticism (t-statistic: −3.17; sig. 0.002; $N = 179$); IT_prop = the proportion of ICT professionals (t-statistic: 2.20; sig. 0.030; $N = 179$); and Arts_abs = the absolute number of artists (t-statistic: −3.85; sig. 0.000; $N = 179$).

There were three indicators that predicted innovativeness in our combined spatial lag-model 6 (Table 3). Indicators that influence innovativeness, including neighbouring areas, are: LIS = lagged innovation score itself (z-value: 4.800; sig. 0.000; $N = 179$); IT_abs = The absolute number of ICT professionals (z-value: 6.82; sig. 0.000; $N = 179$); R_D_abs = The absolute number of R&D professionals (z-value: 11.02; sig. 0.000; $N = 179$); Arts_abs = the absolute number of artists (z-value: −4.93; sig. 0.000; $N = 179$).

As a summary of the results, it is easy to see that the same indicators have the greatest significance regardless whether they are used in OLS or spatial lag models. Spatial lag models provided the highest explanative power (model 6 has the highest R-square value 0.882). The results indicate that areas benefit, in terms of innovation, if they are tolerant (immigration criticism t-statistics are significantly negative in OLS models 2 and 5). This is not a surprising result compared to the significant negative t-statistics of the absolute number of artists in models 1, 3, 5 and 6, in which the variable was included.

The results show that spatial autocorrelation exists to some extent in the HMA. This corresponds with the conclusion that human capital in neighbouring areas is important for growth (Simonen & McCann, 2008). Adding one layer of neighbouring areas contributed an additional 9% of explanative power to the models. Adding the second contiguity layer had no significant effect on the results. Instead, explanation levels dropped approximately 5% from the highest levels.

4.2. Spatial distributions, area ranks and indicator scores

Our research questions are addressed and answered in this spatial analysis. Firstly, the studied innovation clusters and neighbourhoods (postal code areas) with the highest level of human capital are illustrated in Fig. 1. It is evident that concentrations of innovations are highly correlated with concentrations of human capital. Further, it is evident that innovations and human capital are highly clustered (see combined scores in Table 4). Spatially, one larger cluster is located in Western Helsinki and Eastern Espoo. We called this cluster an innovation horseshoe. Secondly, the predicted postal code areas for potential innovation locations and professional demand locations are presented in Fig. 2 and Table 5. Our cluster identification corresponds with earlier HMA innovation studies (e.g. Inkinen & Kaakinen, 2016), but differentiates largely from earlier HMA housing studies, which have seen low density residential areas as the areas with the highest socioeconomic status (e.g. Vaattovaara, 1998; Vilkama et al., 2014; Kiuru, 2015). Agglomeration of human capital externalities in the most central parts of metropolitan area is also in line with the concept of Smart Café Cities (Fu, 2007).

Fig. 1 and Table 4 indicate both the geographical locations and statistical values of the most innovative and human capital intensive locations within the HMA. The top three locations in both categories are the Helsinki centre, Ruoholahti and Otaniemi (Inkinen, 2015). Also on the broader geographical scale, nationally these three postal code areas present the most prominent locations of innovation and human capital in Finland. Fig. 1 highlights the co-location of innovation and human capital. Geographical contrast is significant if these results are compared to the Fig. 2 and Table 5 that present potential growth areas. The division into Northern and Southern parts and the horseshoe development, following the main ring roads, is clearly visible. A comparison between the categories of Table 5 indicates that different locations are leading their respective fields with dispersed geographies. We interpret this to be an indication of the functionality of our division into current leading innovation hotspots and potential future demand areas.

Negative values on Table 5 concerning innovation potential are interpreted as the potential between the observed spatially lagged employment opportunities, thus the presence of knowledge-intensive businesses, in relation to the persons living in those areas. Potential demand refers to areas that experience more highly skilled residents (high human capital) than the actual presence of knowledge-intensive firms would predict. This is an important observation, as it enables the mapping exercise presented in the Fig. 2.

Table 5
Top 15 predicted innovation and future potential demand postal code areas in the HMA.

Area	Innovation potential	Area	Potential demand
Länsi-Pasila	−1.8009	Pitäjänmäen teollisuus	1.2273
Pikku Huopalahti	−1.4344	Pohjois-Tapiola	1.0421
Eira	−0.6989	Munkkiniemi	1.0241
Laajalahti-Friisinmä	−0.6776	Pohjois-Leppävaara	0.9106
Jätkäsaari	−0.6535	Meilahden sairaala-alue	0.8069
Helsinki Keskusta	−0.5592	Westend	0.7173
Punavuori	−0.5436	Ruoholahti	0.6575
Kulosaari	−0.5292	Nihtisilta	0.6325
Vattuniemi	−0.4615	Pajamäki	0.5893
Jokiniemi	−0.4333	Oitmäki	0.5782
Kaivopuisto	−0.4301	Vantaanpuisto	0.4788
Puolarmetsän sairaala	−0.4051	Kirkonkylä-Veromäki	0.4562
Espoon Keskus länsi	−0.3516	Tapiola	0.4559
Kuurinniitty	−0.3456	Hämevaara	0.4299
Kivihaka	−0.3295	Viikki	0.4291

The final interpretation concerning Tables 4 and 5 is that the relative distance in the combined performance of innovation and human capital is dualistic. Thus, there are two clear groups identifiable in Table 4. First, the top three received a combined score close to a value of 10. All the other top areas had significantly lower scores and their values were close to each other. In other words, their relative distances are short in our variable metrics. We can interpret this result as empirical evidence of a strong clustering tendency concerning innovation and human capital: it is likely that cities are able to support a limited number of high-end hotspots in this field. We consider this result to be valid at least for cities close to the size of HMA (population approx. 1 to 1.5 million).

5. Discussion and conclusions

The results of this study contribute to the international debate dealing with the presence of human capital in innovation clusters. First, the results indicate that human capital-driven innovation clustering is a localised intra-metropolitan phenomenon. In general, knowledge-intensive firms locate in proximity to highly skilled workforces within the HMA. The second conclusion is that the measurement of innovations should include a rigid distinction between relative and absolute variables with the consideration of innovation input and output proxies. Similarly, in the prediction of locational innovativeness, relative and absolute indicators of human capital are also important. Interestingly,

Table 4
Highest 15 ranking postal code locations in the HMA in terms of combined innovation and human capital scores.

Combined area rank	Total score	Innovation rank	Innovation score	Human capital rank	Human capital score
Helsinki Center	11.93	Helsinki Center	5.57	Helsinki Center	6.35
Ruoholahti	10.32	Ruoholahti	5.56	Ruoholahti	4.76
Otaniemi	9.40	Otaniemi	4.83	Otaniemi	4.56
Pitäjänmäen teollisuus	6.46	Pitäjänmäen teollisuus	3.89	Etelä-Leppävaara	2.64
Etelä-Leppävaara	5.51	Etelä-Leppävaara	2.87	Pitäjänmäen teollisuus	2.56
Pohjois-Tapiola	3.79	Pohjois-Tapiola	2.46	Länsi-Pasila	2.24
Etu-Vallila	3.61	Itä-Pasila	1.91	Eira	1.81
Itä-Pasila	3.50	Etu-Vallila	1.91	Vattuniemi	1.72
Punavuori	3.20	Kaartinkaupunki	1.75	Punavuori	1.72
Kaartinkaupunki	3.18	Munkkiniemi	1.56	Etu-Vallila	1.70
Vattuniemi	3.17	Nihtisilta	1.52	Itä-Pasila	1.59
Eira	2.82	Punavuori	1.48	Kaartinkaupunki	1.43
Niittykumpu	2.62	Vattuniemi	1.45	Pohjois-Tapiola	1.33
Nihtisilta	2.40	Niittykumpu	1.44	Pikku Huopalahti	1.24
Munkkiniemi	2.16	Eira	1.01	Niittykumpu	1.19

often-used indicators such as the relative number of tertiary degrees, the absolute and relative number of citizens aged 35–44, and the relative number of artists, are not statistically significant factors in any of our models. In fact, the absolute number of artists correlated negatively with innovativeness. The number of artists may prove to be more significant if broader spatial categories are applied, but as the analysis has shown, their presence does not contribute to clustering on a small scale such as postal codes.

In addition to traditional innovation and human capital indicators obtained from earlier literature, a new indicator was collected and applied, namely the popularity of immigration-critical parties. The reason for this was to establish an insight into the spirit of innovative tolerance. Popularity of the immigration-critical parties proved to measure areal tolerance as the proportion of votes for immigration-critical parties correlated negatively with innovativeness. We also wanted to use the number and proportion of students involved, which may be considered an unconventional measure.

The empirical results illustrate that absolute variables are significantly more effective than relative indicators. The dominance of absolute indicators in both innovativeness and human capital suggest that urban density is an essential, and often underrated, circumstance for innovative growth. Considering planning and the mixed land use paradigm, the results show clearly that innovations emerge the best in dense and mixed urban structure.

The analysis identified biases in the balance between housing and knowledge-intensive establishments. Thus, innovation prone and innovation averse postal codes were interpreted as being areas with innovation potential and areas with future demand for skilled professionals. Clusters of innovation and human capital, and clusters with potential growth characteristically form a larger spatial entity (an innovation horseshoe). This finding is in line with the Smart Café City concept (Fu, 2007), where human capital externalities are highly localised in the most central areas of the metropolitan areas.

The city of Helsinki is currently planning several inner-city extensions, and this analysis indicates that they could start from Southern, Eastern and Northwest locations, which could benefit from the zoning of commercial space. Housing development could succeed particularly on the Western shore of the inner city (Ruoholahti to Pitäjänmäki). The most promising part of the surrounding city of Espoo is the Eastern part of the city. These locations are also tightly connected to the centre of Helsinki via a metro line, a commuter train line and an extensive road infrastructure (ring roads one and two). According to our results, these areas could attract additional professionals. Also in the Western part of the city of Espoo, there is a cluster for potential housing. The third large city belonging to the HMA (Vantaa) has three larger clusters for potential growth: a postal code close to the International Airport, which could benefit from housing development; and Eastern and Western clusters, which could benefit from the zoning of commercial space. Development actions from business services officials could also help these emerging locations to grow.

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