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SPATIAL AND COMMUTING NETWORKS: A UNIFYING PERSPECTIVE

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1 Introduction

A wide literature is devoted to the study of the relevance of space, encompassing several fields and disciplines, such as geography, economics, epidemiology, environmental and regional sciences. For example, space-time modelling has been a relevant focus of research in spatial economics starting from Hagerstrand (1967) and Wilson (1967; 1970). While the former paid attention to the modelling of spatial diffusion phenomena, the latter unified movements of spatial flows under the umbrella of statistical and information theory, by means of spatial interaction models. In these models, the relevance of spatial structure emerged in the associated cost/impedance functions. In parallel, starting from Zipf (1932) and Simon (1955), the importance of spatial structures (homogeneous or heterogeneous) has been discussed extensively in the literature, by focusing on the relationships between urban growth, agglomeration economies, and commuting costs (see, among others, Krugman 1991; Rossi-Hansberg and Wright 2006). A point of concern is that, in these spatial (growth and interaction) models, the effects of spatial topology and connectivity are only implicitly included, but never explicitly considered and discussed.

Tied to the spatial topology and connectivity issue is the network concept, which received a great deal of attention in social sciences and spatial economics in the past decades. Examples are the popular ideas of social complex networks (Barabási 2003; Vega-Redondo 2007), the network economy (Shapiro and Varian 1999), and the knowledge economy (Cooke 2001). Networks are based on the existence of interactions – at multiple levels/layers – between agents, giving rise to synergy effects. The effects of these interactions are often investigated and modelled in the form of, for example, network externalities or spillover effects (Yilmaz et al. 2002). The labour market literature is no exception: spatial matching processes have been widely studied in a social network framework (Montgomery 1991), as well as commuting, which has been modelled in both urban and regional contexts (for example, see van Nuffel and Saey 2005; Russo et al. 2007; Reggiani and Bucci 2008). In addition, network-based results can be tied to widely used econometric techniques (see, for instance, the relation between topological accessibility and spatial weights matrices, discussed in Mackiewicz and Ratajczak 1996).

The commuting literature has long been interested in problems of urban shape and regional networks of cities, in particular with regard to monocentricity and polycentricity (Button 2000). Cases of the latter are found at increasingly larger spatial scales, leading to the idea of ‘network cities’ (Batten 1995), in which horizontal city-relations emerge (Wiberg 1993; van der Laan 1998), also because of improved transportation infrastructure and accessibility. In this framework, network modelling approaches to the analysis of commuting flows are worth noting. Russo et al. (2007) analyse commuting flows in

Germany to identify ‘entrepreneurial cities’ in Germany. van der Laan (1998) and van Nuffel and Saey (2005) investigate the emergence of multinodality in the Netherlands and in the Flanders, respectively. In particular, van der Laan finds that increasing horizontal relations emerge for regions with modern economic structures, while the hierarchical status quo is preserved for peripheral, less advanced regions.

In line with the above developments, the present paper investigates, for the case of Germany, the relevance of the volume and distribution of commuting flows, as well as of the commuting network’s connectivity and topology. We aim to assess how network topology and its changes over time affect the geographic commuting system and its hierarchies. The reason for studying the commuting network in a connectivity perspective is inspired by the idea that the distribution of commuting can help explain other relevant economic phenomena, such as the convergence or divergence of labour market indicators (see for example Patacchini and Zenou 2007) or production levels. In this regard, the value added of network analysis is that it allows inspecting – in an intuitive fashion – commuting-induced topology and accessibility. Therefore, we aim to further inspect the connectivity perspective, to improve our understanding of the spatial-economic perspective.

The paper is structured as follows: Section 2 briefly reviews recent developments in the field of network analysis. Section 3.1 illustrates a preliminary spatial analysis of commuting flows in Germany, with reference to the ‘open’ cities (that is, to the cities with high propensity to mobility), while Section 3.2 presents the results of the network modelling experiments, by focusing on the network connectivity properties. Section 4 presents then a comparative multicriteria analysis that synthesizes the dynamics of the different hierarchies – concerning the German ‘open’ districts – emerging from the spatial and network approach. Finally, Section 5 concludes the paper with some final remarks and directions for future research.

2 Spatial and Network Analysis: Recent Perspectives

Recent developments in spatial analysis call for a better understanding of the influence of space in the dynamics of economic growth patterns (for example, agglomeration economies). Relationships between agglomeration economies, fractal patterns, and rank size rules can be found, among others, in Batty (2005), and Chen (2004), while spatial equilibrium models consisting of a system of monocentric cities (city network) have also been adopted (see, for example, Abdel-Rahman 2003). However, these models have rarely embedded network concepts.

Here below we briefly discuss recent developments in network analysis and, in particular, their implications for regional networks. The focus is on recent works published by Barabási and Albert (BA) (1999), which radically changed the pre-existing frameworks for the analysis of large networks, by developing the concept of ‘scale-free (SF) networks’, and by providing a model that helps explaining their (topological) properties.

SF networks are usually discussed vis-à-vis ‘random networks’ (see, for example, the conventional Poisson random graph, Erdös and Renyi 1960). SF networks – first formalized by Price (1965; 1976) – are characterized by the presence of a few nodes (‘hubs’) with a high number of connections (‘links’) to other nodes (a high ‘degree’), and by the a vast majority of nodes exhibiting a low number of links. The term ‘scale-free’ refers to the statistical properties deriving from the above characteristics (see Newman 2003) and implies a great heterogeneity of the degree distribution.

The probability distribution of the nodes’ degree x (its ‘degree distribution’) for SF networks tends to decay following a power function:

$$\Pr(X = x) \sim x^{-a}, \tag{1}$$

For large x, the value of the exponent a in SF networks converges to 3 (Bollobás et al. 2001). A direct relation follows between the power law and Zipf's law (Zipf 1932), a distribution relating the degree of the nodes to their rank (Adamic 2000). According to Zipf, the relation between these two variables is as follows:

$$x \sim r^{-b}, \tag{2}$$

where r is the rank of the node concerned. The value of the exponent b is expected to be 1. Following from the mathematical relation of the Pareto distribution (which can be interpreted as rank size rule) and power-law distributions (Adamic 2000), the relation between Equations (1) and (2) is given by:

$$a = 1 + 1/b. \tag{3}$$

On the basis of the above considerations, we apply – in our empirical experiments – Equation (2) (in logarithmic terms), by then extrapolating the value of a according to Equation (3).

In contrast to SF models, random networks (RNs) belong to a long-established class of networks (Rapoport 1957; Erdös and Renyi 1960). In an RN, the links between nodes in the network are expected to arise randomly. As a result, the probability of a node having degree x, $\Pr(X = x)$, follows, for a large-enough number of nodes, a Poisson distribution, implying a homogeneous distribution of connections. Consequently, most of the nodes have a similar number of links and importance.

In our empirical application, we test whether the German commuting network shows SF or RN characteristics, that is, if it is heterogeneous or homogeneous. Consistently with Equation (2), we adopt, in the RN case, the exponential Equation (4), where the degree of the nodes x is sorted in decreasing order:

$$x = ke^{-\beta r}. \tag{4}$$

By synthesizing, the empirical evidence of rank size rules in urban economics, biology, and other fields is strictly related to the underlying connectivity network properties expressed by the associated power law. In other words, the rank size rule advocated in spatial economic science and the power law advocated in social sciences can be considered as two sides of the same coin, and hence interpreted in a unifying perspective.[1]

The above analytical frameworks are tested, for the case of the German commuting network, in Section 3.2, subsequently to a preliminary spatial analysis.

3 Case Study: Dynamics of German Commuting

3.1 Spatial Analysis: The 'Open Cities'

Before analysing the network properties of spatial commuting patterns, we will synthesize the characteristics of the German database from a regional/spatial perspective.

The data employed in our analysis refer to the registered residence and workplace of all dependent employees in Germany, at two points in time: 1995 and 2005. The data are aggregated in 439 German administrative districts, called *Kreise* (NUTS-3), and were collected by the Federal Employment Services (*Bundesanstalt für Arbeit*, BA) within social security services.[2] We can then form an origin-destination (OD) matrix, of dimension 439 x 439, which has, for each cell (i, j), the number of employees living in

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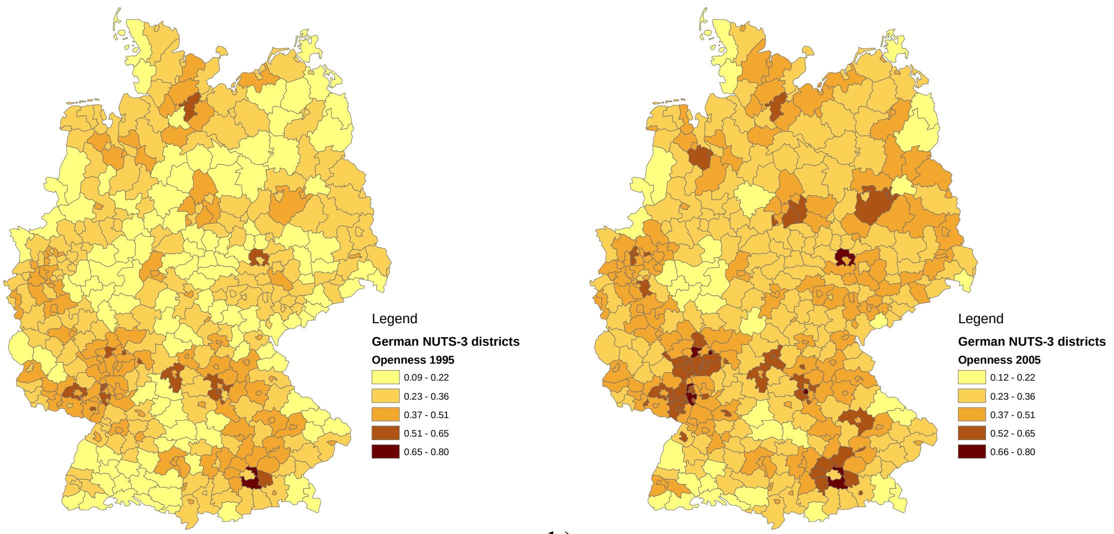
1 See also Chapter 19 by Reggiani, in this volume.

2 Since the data are directly gathered at the single firm level, it is reasonable to expect low and non-systematic measurement errors.

district i and working in district j. In addition, we classify the German districts with regard to their levels of urbanization and surrounding agglomeration[3] (BBR– *Bundesanstalt für Bauwesen und Raumordnung*) (Böltgen and Irmen 1997).

As indicators of the propensity to mobility of the districts, we employ indicators of incoming and outgoing mobility, which we refer to as inward and outward openness (authors' adaption from van der Laan 1998). The inward openness of a district indicates to which extent it attracts outside workers, and is computed, for a generic district j, as the ratio between the number of employees of the district j residing in other districts, and the total number of employees of district j: $\sum_{i \neq j} e_{ij} \Big/ \sum_{i} e_{ij}$. Similarly, the outward openness can be defined as the percentage of residents who commute outside of their district, and is computed as: $\sum_{j \neq i} e_{ij} \Big/ \sum_{j} e_{ij}$. As a synthetic indicator of mobility (openness), we compute the average of inward and outward openness. This synthetic openness measure represents the capacity of a district to be 'mobile' and, consequently, 'active'. van der Laan (1998, p. 238) identifies high values of openness as possible signs of a 'multi-nodal urban region'.

In Figure 1, central cities (CBDs) and highly urbanized districts mainly emerge as the most 'active' in both 1995 and 2005. The Munich *Landkreis* resulting as the most 'open'. The higher concentration of population and economic activities (located within or in the surroundings of the main cities) – or a mobile population exploring new work opportunities – might explain this result (van Oort 2002). Notable exceptions – with low openness values – are Berlin and CBD of Munich, due to the larger areas, which tend to contain commuting with the district boundaries. Over the ten-year period we observe a generalized increase in the propensity to mobility, while a bigger positive variation can be found for the Berlin area.



a) b)

Source: Patuelli et al. (2009).
Figure 1 – Maps of openness of districts, 1995 and 2005

3 The districts are classified as follows: 1) central cities in regions with urban agglomerations; 2) highly urbanized districts in regions with urban agglomerations; 3) urbanized districts in regions with urban agglomerations; 4) rural districts in regions with urban agglomerations; 5) central cities in regions with tendencies towards agglomeration; 6) highly urbanized districts in regions with tendencies towards agglomeration; 7) rural districts in regions with tendencies towards agglomeration; 8) urbanized districts in regions with rural features; and 9) rural districts in regions with rural features.

In this context, it could be interesting to explore whether the most 'open' cities seen above are also connected together in a city-network pattern. In summary, given the mobility characteristics of the districts, it might be relevant to explore how these are affected by the underlying connectivity networks, also in the light of the findings supporting multinodality, recently presented in the literature (Batten 1995; van Nuffel and Saey 2005). The next section investigates this aspect.

3.2 Network Analysis: The 'Connected' Cities

3.2.1 Connectivity Distribution

An initial analysis of the network underlying the commuting activities can be carried out by considering the statistical distribution of the data. In order to identify the (network) attractiveness and the propensity to mobility of the districts, we propose two exploratory approaches, based on the so-called indegree and on the inward openness. First, the number of inward connections per district (*indegree*) is examined, that is, from how many districts commuters come. From this viewpoint, which regards the logical topology of the commuting network, it is relevant *if* there is (any) commuting between two districts i and j, whatever its extent. Secondly, we examine the inward openness of the districts (as defined above). In this case we consider the commuting inflows, that is, the weights tied to the links. In this case, the total inflows of each district are standardized by the number of jobs available in-place.

We next interpolate our data with a power function and an exponential function (see Equations (2) and (4)). Table 1 shows the resulting R^2 coefficients and the values of the function exponents. For the case of the indegree distribution, an exponential distribution fits well the degree decay, although with a sharp cut-off at the end, and its exponent also remains extremely low in time. The R^2 for the power function is lower and also decreasing over time. On the other hand, its coefficient is more meaningful from an economic point of view. Transforming the indegree power-law coefficient according to Equation (3), we obtain coefficients much greater than 3, suggesting random network characteristics (that is, a homogeneous pattern). Overall, these findings suggest the existence of a highly interconnected (logical) commuting network. However, the ambiguity between exponential and power law suggests that no clear agglomeration-pattern can be inferred in the case of the indegree distribution.

Table 1 – R^2 values and exponents for power and exponential interpolations of incoming connections (indegree) and inward openness, 1995 and 2005

Year	*Indegree*		*Inward openness*	
	Power law	Exponential	Power law	Exponential
1995	0.7002	0.9739	0.8027	0.9871
(exponent)	(0.2442)	(0.0022)	(0.4623)	(0.0039)
2005	0.6046	0.9316	0.7820	0.9859
(exponent)	(0.2589)	(0.0025)	(0.4000)	(0.0034)

Source: Patuelli et al. (2009).

As for the indegree distribution, the distribution of the inward openness remains fairly stable in the two years considered, and the exponential function better interpolates the data. However, the power function also has a high R^2. In addition, the exponent values for the power interpolation are now higher (0.40–0.46), which implies transformed power-law coefficients greater than[4] 3. Overall, this preliminary data exploration shows that the exponential function is a better fit to both the indegree and the inward openness distributions, thus suggesting – according to these variables – an equilibrated network. This result is indeed in agreement with the associated rank size rule (Equation (2)), since power-law coefficients smaller than 1 indicate an even spatial distribution of the two variables at hands (indegree and openness) (Brakman et al. 2001).

3.2.2 Network Indices

After exploring the data and their distribution, we provide a set of synthetic indices, which describe three principal aspects exploring the network under different perspectives: (a) centralization; (b) clustering; and (c) variety/dispersion.

Network centralization is an aggregate assessment of the degree of inequality of a network. It may be computed on the basis of individual node centrality measures. The 'centrality' of a node may be seen as a measure of its structural importance. The centrality index presented here may be called *indegree centralization*, and is based on the concept of relative degree centrality of nodes, which measures the 'visibility' of a node. This concept can be linked to the one of 'hub' (Latora and Marchiori 2004), since the most visible nodes can be considered as hubs. The index only considers direct connections (indirect connections can only be considered if the transportation infrastructure is included in the analysis), and, in our case, only inward connections are considered (hence, the denomination 'indegree centralization'), in order to show the nodes' attractiveness for outside workers. Relative indegree centrality (ric_i) is computed, for each node i, as the ratio between the observed and the maximum possible number of connections of a node (n – 1): $ric_i = \text{indegree}_i /(n-1)$, where n is the total number of nodes. Consequently, the aggregate network indegree centralization (*NIC*) index is computed, similarly to Freeman (1979), as: $NIC = \sum_{i\in N} (ric^* - ric_i) \big/ (n-2)$, where ric^* is $\max_i (ric_i)$.

The second index we compute refers to network clustering. Network clustering coefficients have been used extensively in network analysis (see, for example, Watts and Strogatz 1998) in order to determine the level of interconnectedness of networks. In order to compute a clustering coefficient for a node, we need to define its neighbourhood, which is given – if first order relations only are considered – by the nodes directly connected to the node concerned. A clustering coefficient for node i is then computed as the ratio of the number of links existing between its neighbours and the maximum number of links that may exist between the same (neighbours): $c_i = l_i \big/ l_i^*$, where l_i and l_i^* are the actual and possible number of links in node i's neighbourhood, respectively. A synthetic network clustering coefficient is then computed as the average of the single nodes' coefficients. Clearly, if n-order neighbours are considered, a node's neighbourhood is represented by all the nodes that can be reached in n hops.

As a third index, in order to assess the variety/dispersal of the nodes, we use an entropy indicator. Entropy is a concept derived from information theory (Shannon 1948) and widely used in spatial-economic science (Wilson 1967, 1970). Entropy is employed here as an indicator of the probability that the flows observed are generated by a 'stochastic spatial allocation process' (Nijkamp and Reggiani 1992, p. 18). Higher entropy levels indicate that the flows are more homogeneous and dispersed over the network. The indicator E is

[4] Our result would vary if we imposed a minimum threshold on the flows associated with each network link. A threshold set at 3 would support a finding of scale-free characteristics of the commuting network.

computed as: $E = -\sum_{ij} p_{ij} \ln p_{ij}$, where $p_{ij} = t_{ij} / O_i$. In p_{ij}, t_{ij} is the number of commuters between districts i and j, while O_i is the outflows of district i.

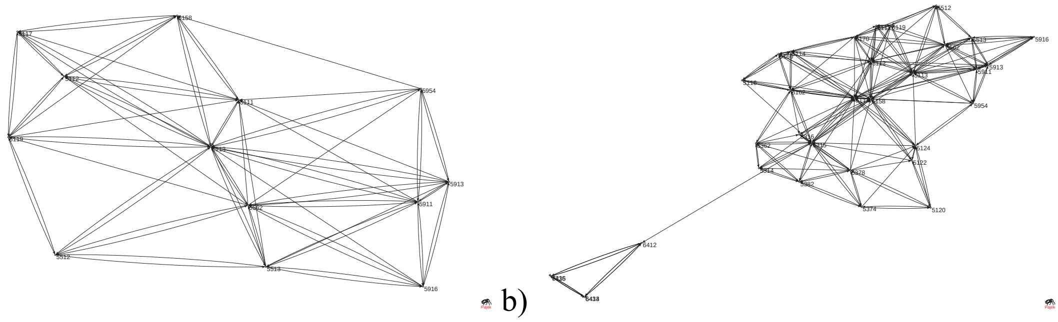
Table 2 presents the results obtained for the German commuting network for the three indices described above, for the years 1995 and 2005. Though without dramatic changes, the network shows two distinct trends over ten years. On the one hand, the network becomes less centralized, while the entropy increases. These results imply a more distributed structure of the network. On the other hand, the clustering coefficient of the network grows, suggesting a tendency towards greater interconnectivity. These results seem to confirm the findings emerging in our spatial analysis (Section 3.1), highlighting the network's tendency towards a multinodal structure (van der Laan 1998).

Table 2 – Descriptive indices for the German commuting network, 1995 and 2005

Indices	*1995*	*2005*
Indegree centralization	0.33	0.31
Clustering	0.59	0.63
Entropy	8.23	8.38

Source: Patuelli et al. (2009).

A graphical representation of the tendency towards greater interconnectivity in the commuting network can be obtained, for 1995 and 2005, on the basis of the '*k*-core' concept (Figure 2), again from an *inward connections* viewpoint. A *k*-core is a subgraph (or more) in which each node has a minimal degree (in our case, *indegree*) of *k*, that is, each node in the *k*-core has connections with at least *k* other nodes in the subgraph (Holme 2005). For a more meaningful computation and a readable graph, we select a subsample of the data, consisting of the flows above the arbitrary threshold of 1,000 individuals per OD pair. We find – for both 1995 and 2005 – *k*-cores of level 4, comprising first 13 and then 33 districts.


a) b)

Source: Patuelli et al. (2009).
Figure 2 – '4-cores' in the commuting network: (a) 1995; (b) 2005

For the year 1995, the small core of 13 districts identifies a local and heavily interconnected network, headed by Düsseldorf and Dortmund, showing intense horizontal (local) relations. The fact that other districts do not appear in the 4-core does not mean that they have no reciprocal flows of commuters with the core districts. Simply, these other nodes do not feature the minimum levels of interconnectedness and flows of the core nodes, although they can show several flows much greater than 1,000 individuals. Frankfurt is a clear example. If we consider the year 2005, a larger graph of 33 districts is found. Here, the Düsseldorf/Dortmund cluster increases, and it represents most of the core. But it is noteworthy to cite the function of Frankfurt, which now acts as a hub, connecting the Frankfurt (code 6412) local cluster to the main Düsseldorf/Dortmund cluster.

Overall, the results of the network analysis seem to confirm the multinodal structure of the German commuting network (especially at the local level), while also suggesting an increased connectivity among the major centres – as centrality decreases over time – and, consequently, a tendency towards two layers of multinodality: (a) at the local level; and (b) at the regional level (the city-network level). As also seen by van Nuffel and Saey (2005, p. 326) and by van der Laan (1998, p. 244), these relations between the main centres do not overshadow local links – which still carry most of the mobility – but complement them.

4 Multidimensional Synthesis: The Network of the 'Open' and Connected Cities

As a final step of this research endeavour, it is worthwhile to map out the hierarchies of the districts and their persistence over time, in order to identify the main relevant centres from both a spatial and a network viewpoint. We aim to offer a 'synthetic' measure of the multiple spatial and connectivity dimensions observed above, by using a multidimensional method well known in the spatial-economic literature, known as multicriteria analysis (MCA). The synthetic assessment of the district characteristics – from the spatial and the connectivity perspectives – allows us to define a dominance rank of the districts concerned, and to investigate the changes which occurred in this rank over the period 1995–2005.

In order to look at the most representative districts only, we select a subsample of districts ('alternatives') to be employed in our MCA, using a synthetic connections-flows (CF) index, computed, for each district *i*, as $(CF)_i = [C_i / \max_i(C_i)] * [F_i / \max_i(F_i)]$, where C_i and F_i are the number of incoming connections (the indegree) and the inward openness of district *i*, respectively. The index is the product of the two normalized indicators C_i and F_i, and is constrained from 0 to 1. It aims to provide a balanced assessment of the openness and connectedness of the districts, that is, from the conventional spatial interaction perspective and from the network perspective, respectively. On the basis of the CF index, we select 26 districts (listed in Table 3), which appear among the top 30 districts for both 1995 and 2005. Such a large group of 'open' districts (26 of 30) over a 10-year period suggests an overall stability of the upper tier of the districts, according to the CF index. The districts selected, with a few exceptions, are urban districts – that is, central cities of type 1 and 5.

We carry out the MCA[5] on the basis of two aggregate assessment criteria (macro-criteria): spatial mobility (inward and outward openness) and connectivity (relative indegree centrality and clustering coefficients). We proceed in two steps: first, by carrying out an MCA for each macro-criterion[6] and, second, by carrying out a final MCA which synthesizes the two previous analyses.

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[5] We employ the regime multicriteria method Hinloopen and Nijkamp 1990). In detail, three scenarios have been considered: (a) equal weights to all criteria; (b) ascending weights; and (c) descending weights. A final MCA of the rankings obtained provides the final results. We assume the hypothesis of no correlation between the criteria employed in the MCA.

[6] The two macro-criteria employed here clearly identify two different types of phenomena: Spearman's correlation between the rankings resulting from the spatial and connectivity MCAs is equal to –0.369 for 1995 and to –0.311 for 2005. This is confirmed by the cross-correlations between the spatial and the connectivity criteria, which range – in absolute values – from 0.066 to 0.501.

Table 3 – Multicriteria analysis for the ‘open’ and connected districts: results for 1995 and 2005

Districts	*Spatial results*		*Districts*	*Connectivity results*		*Districts*	*Final results*	
	1995	2005		1995	2005		1995	2005
09184 Munich	1	1	05111 Düsseldorf, Stadt	1	1	09184 Munich	1	1
06436 Main-Taunus-Kreis	2	2	06412 Frankfurt am Main, Stadt	2	2	06436 Main-Taunus-Kreis	2	4
09661 Aschaffenburg, Stadt	3	4	08111 Stuttgart	3	4	06411 Darmstadt, Stadt	3	3
06413 Offenbach am Main, Stadt	4	3	09184 Munich	4	7	07315 Mainz, Stadt	4	5
06411 Darmstadt, Stadt	5	5	09564 Nuremberg, Stadt	5	8	08221 Heidelberg	5	9
07314 Ludwigshafen am Rhein, Stadt	6	6	05314 Bonn, Stadt	6	9	05314 Bonn, Stadt	6	7
08221 Heidelberg	7	8	08222 Mannheim	7	6	06414 Wiesbaden, Landeshauptstadt	7	2
07315 Mainz, Stadt	8	7	06414 Wiesbaden, Landeshauptstadt	8	3	09562 Erlangen, Stadt	8	15
09662 Schweinfurt, Stadt	9	15	06436 Main-Taunus-Kreis	9	11	08121 Heilbronn	9	16
08121 Heilbronn	10	9	08212 Karlsruhe	10	5	07314 Ludwigshafen am Rhein, Stadt	10	18
09461 Bamberg, Stadt	11	12	06411 Darmstadt, Stadt	11	10	08421 Ulm	11	12
08421 Ulm	12	11	07315 Mainz, Stadt	12	13	06412 Frankfurt am Main, Stadt	12	8
09562 Erlangen, Stadt	13	10	09562 Erlangen, Stadt	13	12	06413 Offenbach am Main, Stadt	13	10
06611 Kassel, Stadt	14	16	08221 Heidelberg	14	15	08222 Mannheim	14	6
07111 Koblenz, Stadt	15	13	08421 Ulm	15	14	08111 Stuttgart	15	11
06414 Wiesbaden, Landeshauptstadt	16	14	08121 Heilbronn	16	20	06611 Kassel, Stadt	16	17
05314 Bonn, Stadt	17	17	09663 Wuerzburg, Stadt	17	22	09661 Aschaffenburg, Stadt	17	20
09362 Regensburg, Stadt	18	20	07314 Ludwigshafen am Rhein, Stadt	18	21	05111 Düsseldorf, Stadt	18	13
09161 Ingolstadt, Stadt	19	24	06413 Offenbach am Main, Stadt	19	16	09663 Wuerzburg, Stadt	19	24
09663 Wuerzburg, Stadt	20	19	06611 Kassel, Stadt	20	17	07111 Koblenz, Stadt	20	22
08222 Mannheim	21	18	09161 Ingolstadt, Stadt	21	18	08212 Karlsruhe	21	14
06412 Frankfurt am Main, Stadt	22	22	09362 Regensburg, Stadt	22	19	09564 Nuremberg, Stadt	22	19
08111 Stuttgart	23	21	07111 Koblenz, Stadt	23	24	09461 Bamberg, Stadt	23	25
05111 Düsseldorf, Stadt	24	25	09661 Aschaffenburg, Stadt	24	23	09161 Ingolstadt, Stadt	24	23
08212 Karlsruhe	25	26	09461 Bamberg, Stadt	25	25	09362 Regensburg, Stadt	25	21
09564 Nuremberg, Stadt	26	23	09662 Schweinfurt, Stadt	26	26	09662 Schweinfurt, Stadt	26	26

Source: Patuelli et al. (2009).

[a] Spatial criteria: inward and outward openness

[b] Connectivity criteria: relative indegree centrality and clustering coefficient

[c] Final MCA: uses as criteria the spatial and connectivity results.

With respect to the MCA based on spatial-economic indicators (spatial mobility macro-criterion), the results (presented in Table 3) show that Munich (*Landkreis*) steadily occupies the first position. Moreover, the ranking of the top districts is rather stable over the period considered. The results of the second MCA, based on the connectivity macro-criterion, provide – in 1995 – a different ranking, as the main cities are dominant. As seen earlier for the *k*-core analysis, Düsseldorf emerges from a network perspective. Further large cities, such as Frankfurt, Stuttgart and Munich, follow. We can also note that, with the exception of Munich, the districts that headed the spatial MCA rankings only perform intermediately in the connectivity MCA.

The final MCA results, synthesizing the two preceding analyses, can be summarized along a few main observations. The district of Munich (*Landkreis*) – which also happens to be the richest German district according to per capita GDP – emerges as the most dominant for both 1995 and 2005, while a reshuffling in the rank of the districts can be observed over the 10-year period. Other districts seem to emerge. In particular, these are: Wiesbaden (from 7th to 2nd), Mannheim (14th to 6th), Frankfurt (12th to 8th), Stuttgart (15th to 11th), Düsseldorf (18th to 13th) and Karlsruhe (21st to 14th). The progress observed for these districts is mainly due to the connectivity macro-criterion. In other words, their high clustering coefficients show that the above districts are oriented towards stronger agglomeration patterns, in addition to their openness.

The findings summarized here lead us to propose a reinterpretation (or integration) in an economic sense of the concept of hub (for conventional hub definitions, see Barabási 2003), on the basis of a node's capacity of not only attracting connections from many other nodes, but also of generating an increased propensity to mobility. This double role by a few main nodes may drive the network towards multinodal characteristics.

However, although the districts emerging in the above analysis are the most 'open' and 'active', they still cannot be considered as the main 'attractors'. If we want to explore this characteristic, we then have to use, in the CF index computation, different variables (such as inflows or workplaces), in order to detect the relevance of the destinations, as the attraction models in the transport literature suggest.[7]

5 Conclusions

This paper has attempted to provide a novel analysis of commuting data and their trends, investigating both the spatial distribution of work mobility and the underlying logical commuting network. We have analysed data on journey-to-work trips for 439 German districts, for the years 1995 and 2005.

From a spatial perspective, we searched for the most mobile and 'open' centres, with a particular focus on the openness of different typologies of districts. From the network perspective, we first considered the distributional properties of mobility indicators such as inward openness and indegree. We then computed aggregate indicators showing the evolution of the commuting network structure. Overall, we found evidence of the presence, in addition to a local and strongly interconnected network, of a *regional* network, which, however, does not overshadow established local patterns (see, for example, the results of the *k*-core analysis).[8]

[7] In this context, had inflows and outflows been employed as criteria within the spatial mobility macro-criterion, a ranking similar to the one obtained for the connectivity macro-criterion would have emerged.

[8] If high-degree nodes were found to be also connected to each other, then highly interconnected clusters could emerge, possibly leading, according to Holme (2005), to a core-periphery network structure (Chung

In order to provide a unifying perspective, we synthesized the two (spatial and network) analyses by carrying out a multicriteria analysis (MCA). The MCA allowed us to observe, through a systematic assessment of the various indicators computed that the German districts are stable at the spatial mobility level, that is, with regard to their hierarchies. In addition, the results of the connectivity-based MCA show that the clustering coefficient indicator appears to influence most network connectivity, as suggested by Watts and Strogatz (1998).

A number of further research directions can be traced, in order to push further (or to fully exploit) the multidisciplinarity of the analytical approach proposed here. From the theoretical viewpoint, a deeper investigation of the influence of distance, travel time and accessibility, as well as of labour market characteristics, on commuting would be commendable. In this regard, and in order to better understand the relationship between the spatial economy and its underlying interaction networks, further research should frame our approach within more extensive regional labour market theoretical models (for example, the one developed by Blanchard and Katz (1992)). A further investigation of local commuting networks and agglomeration economies could be sought by integrating power-law-based and Zipf's-based evidence. Behavioural analysis at a micro-level (or taking into account different socio-economic groups) would also be fruitful, in order to test the aggregate behaviour.

From the methodological viewpoint, additional topological characteristics, such as betweenness-based centrality measures, should be investigated by means of a joint network/physical infrastructure analysis. Moreover, incorporating physical infrastructure would allow us to fully exploit network analysis tools, and to inspect widely relevant policy issues, such as infrastructure criticalities and bottlenecks. An integration of spatial and network-based measures into spatial econometric interaction models (see, for example, Griffith in this volume) should also be sought, in particular in order to investigate the relationship between clustering and network autocorrelation.

From the empirical viewpoint, the study of pre- and post-unification commuting networks in Germany, as well as of alternative geographical settings (for example, islands; see De Montis et al. in this volume) and aggregation levels, could provide much needed information on the different long-run evolution of commuting networks.

All in all, the integrated 'space-network' approach seems to offer novel pathways for the analysis of commuting and the associated interacting economic activities.

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and Lu 2002). Most importantly, Holme shows that transportation networks (more generically, geographically-embedded networks) tend to share this characteristic.

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