The evolution of the commuting network in Germany

Spatial and connectivity patterns

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Abstract: The analysis of the structure and evolution of complex networks has recently received considerable attention. Although research on networks originated in mathematical studies dating back to the nineteenth century (or earlier), and developed further in the mid-twentieth century with contributions to graph theory, interest in its application to the social sciences is currently growing—particularly in regional science and transportation, because of the spatial relevance of networks. This paper presents a dynamic outlook for the German commuting network from the perspective of the German labor market districts. The focus of this paper is to explore how the German commuting network evolves, from two perspectives: space and connectivity. We consider home-to-work commuters moving between 439 German districts for the years 1995 and 2005. The results of the present analysis make it possible to identify, among the main German districts, the most "open" and connected ones. These emerging districts can be considered as potential "hubs" in the German commuting system—that is, as attractors from the perspective of spatial economics, and as interconnectors from the perspective of networking.

Keywords: Spatial analysis; Network analysis; Commuting; Germany

1 Introduction

Network concepts have received a great deal of attention in spatial economics in recent decades. Examples are the well-known ideas of the network economy (Shapiro and Varian 1999) and the knowledge economy (Cooke 2001). Networks are based on the existence of interactions (which may occur on multiple levels) between agents operating in a network, giving rise to synergistic effects. The effects of these interactions are often investigated and modeled by considering, amongst other things, network externalities or spillover effects (Yilmaz *et al.* 2002). The labor market literature is no exception to this trend: spatial job matching processes have been widely studied in a social network framework (Montgomery 1991), while work-induced

mobility (commuting) has been investigated in both an urban and a regional network context (e.g. Russo *et al.* 2007; Thorsen *et al.* 1999; Van Nuffel and Saey 2005).

The directionality of commuting flows has clear implications for urban form and for the development of regional networks of cities. Commuting has long been studied with these implications in mind, in particular concerning locational and developmental trends leading to either the monocentric (central) city or the polycentric city. [1] The latter perspective has been developed by observing the various deconcentration trends observed in many major cities (e.g. Bar-El and Parr 2003; Fujita *et al.* 1999). These trends are now increasingly evident at larger spatial scales leading, for example, to the idea of "network cities" (Batten 1995). In this context, horizontal relations between cities tend to emerge (Van der Laan 1998; Wiberg 1993). The emergence of network cities also results from improvements in transportation systems and accessibility, which diminish the importance of distance. Remarkably, Papanikolaou (2006) suggests that spatial structure alone does not strongly account for different commuting distances. As a result of the ongoing process described above, local hierarchies—originally consistent with monocentric theories—are subject to constant change and exhibit more decentralized urban regions; examples are the *Randstad* area in the Netherlands (see Clark and Kuijpers-Linde 1994) or the emergence of edge urban areas (edge cities) (see Phelps and Parsons 2003).

In this framework, there have been many experiments with network-modeling approaches to the analysis of commuting flows. Thorsen *et al.* (1999), for instance, examine the effects of transportation infrastructure and spatial structure on commuting flows in a network of cities. Russo *et al.* (2007) use commuting flows in Germany to identify "entrepreneurial cities" in Germany. Van der Laan (1998); Van Nuffel and Saey (2005) investigate the emergence of local and regional multi-nodality for the Netherlands and the Flanders area, respectively, on the basis of commuting flows. In particular, van der Laan finds that more horizontal (non-hierarchical) relations emerge for regions with modern manufacturing systems, while the (hierarchical) status quo is preserved for peripheral, less advanced regions.

On the basis of the aforementioned developments, the present paper investigates, for the case of Germany, the relevance in the first place, of the volume and distribution of the commuting flows, and, in the second place, the connectivity and topology of the same network. In particular, we aim to assess whether the geographic commuting system and its hierarchies, in the years 1995 and 2005, are affected by network topology and its changes over time. In other words, we aim to investigate whether the most mobile districts are also the most connected. Our inspiration for studying the commuting network from a connectivity perspective is the idea that the network distribution of mobility can help explain other relevant economic phenomena, such as variations in key labor market indicators or production levels. The importance of spatial interaction (Niebuhr 2003), and primarily of commuting (Patacchini and Zenou 2007), for the development of regional labor markets has been stressed in the recent literature. Moreover, distance has already been shown to lead to greatly diminished labor market interactions, when over a certain threshold (e.g. Badinger and Url 2002), and accessibility is also seen as a possible source of spatial dependence (Anselin and Florax 1995). In this framework, the value added of network analysis is that its set of analytical tools supports an intuitive inspection of commuting-related topology and accessibility. Given these premises, our aim is to dig deeper in the connectivity perspective in order to improve our understanding of the spatial-economic perspective. The paper is structured as follows: Section 2 briefly describes recent

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[1] For a more extensive review of urban economic theories, see Button (2000); Hall and Pain (2006).

developments in network analysis, on which some of our empirical analyses are based. Section 3 illustrates a preliminary spatial analysis of commuting flows in Germany, while Section 4 presents the results of the network modeling experiment undertaken. Section 5 then presents a comparative multicriteria analysis that addresses the change in hierarchies in the main German districts. Finally, Section 6 concludes the paper with some final remarks and suggestions for future research.

2 New Network Analysis Perspectives

This section briefly discusses recent developments related to the analysis of networks, particularly their implications for regional networks. We focus on recent works published by (Barabási and Albert 1999). Their approach radically changed the pre-existing frameworks of analysis of large networks, by bringing a great deal of attention to the concept of scale-free networks and by providing a model that helps explain the topological properties of such networks.

Scale-free (SF) networks are usually described and analyzed in contrast to random networks (for example, the conventional Poisson random graph; see Erdős and Renyi 1960). SF networks—of which a first formalization was proposed by Price (1965, 1976)—are characterized by the presence of a few nodes (the "hubs") having a large number of connections ("links") to other nodes (a high "degree"), while the vast majority of nodes have few links. The term "scale-free" refers to the distributional properties deriving from the above characteristics (see Newman 2003) and implies a highly heterogeneous degree distribution. The contribution of Price, and of Barabási and Albert (BA), is in providing models that explain the emergence of SF networks, by taking into consideration the growth of the network. In these models, hubs emerge in a network because nodes tend to connect to well-connected nodes—that is, to nodes with a high degree. This mechanism is known, in the BA model, as "preferential attachment."[2]

As a result of this process, the probability distribution of the nodes' degree x (its degree distribution) for SF networks tends to decay following a power function of the type

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

For large values of x, the value of the exponent a in SF networks converges to 3 (Bollobás *et al.* 2001).

According to Adamic (2000), a direct relation follows, from Equation (1), between the power law and Zipf's law (1932), a distribution relating the degree of the nodes to their rank (in the full list of nodes sorted by their degree). According to Zipf, the relation between these two variables is

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

where r is the rank of the node concerned. The exponent b is expected to be equal to 1. Again, in Adamic (2000), Equation (2) will have the same exponent as a Pareto distribution, which explains the rank r by means of the degree x; that is, the axes are inverted, if $b = 1$. Following from the mathematical relation of the Pareto and power-law distributions, any process having a Zipf's distribution ($b = 1$) will have a power-law density function. In this context, Adamic

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[2] Albert and Barabási's concept of preferential attachment is equivalent to Price's "cumulative advantage."

shows that the relation between Equations (1) and (2) is given by

$$a = 1 + \frac{1}{b}. \qquad (3)$$

On the basis of the above considerations, we will consider and apply Equations (2) and (3) in our empirical experiments.

In addition to the aforementioned properties, SF networks are also characterized by high clustering and short average-path lengths. Clustering (see Section 4.3), which is measure of network density, can be expected to be significantly higher than for the case of random networks, which have low clustering values. In particular, clustering will tend to greater values in SF networks that present values of a smaller than 2.3 (Newman 2003). SF networks also exhibit short geodesic paths (that is, the shortest distance, in hops, between two nodes) because the hubs in the networks allow for direct links between clusters, and most peripheral nodes tend to be attached to a strongly connected node. As a result, the structural importance of a randomly selected node is likely to be rather limited and the removal of the node will not significantly increase the shortest paths in the network; conversely, it follows that the few hubs are critical for the network's functioning.

In contrast to SF models are random networks (RNs), which belong to a long-established class of networks originally studied by Rapoport (1957) and Erdős and Renyi (1960). In a random network, links between agents (nodes) are supposed 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; that is, most of the nodes have a similar number of links (close to the average degree) and, consequently, a similar importance (the distribution is homogeneous).

In our empirical applications we will test whether our commuting network shows SF or RN characteristics in order to determine its heterogeneity versus homogeneity. In order to be consistent with Equation (2), we will adopt, in the RN case, the exponential Equation (4), where x is the degree of the nodes, sorted in decreasing order, and r is the rank of each node:

$$x = k e^{-\beta r}. \qquad (4)$$

In recent years, great interest has arisen for the analysis of transportation systems in the framework of complex networks (for an overview, see Reggiani and Schintler 2005). Case studies have been carried out by Amaral *et al.* (2000) for airline networks, as well as by Latora and Marchiori (2002) for the Boston subway, and by Schintler and Kulkarni (2000) with regard to congested road networks. It should be mentioned, however, that the structural limitations of (physical) networks (for example, transport networks)—including limited space and high infrastructure costs—hinder the full emergence of SF properties. Such aspects will be investigated in Section 4 for the case of the German commuting network.

3   Dynamics of Commuting: Spatial Data Exploration

In the preceding section, we illustrated recent developments in the analysis of networks. These tools, in particular the work of Barabási (2003), are among the central ones considered in our study for exploring changes in the characteristics of the German commuting network topology. Before analyzing the network properties of spatial commuting patterns, we present the German database from a regional/spatial perspective.

The data employed in our analysis comprise the locations of residence and workplace for all wage-earning employees (excluding the self-employed) in Germany, for the years 1995 and 2005. The data are aggregated at the NUTS-III level of the EU geocoding system (that is, German administrative districts, called *kreise*), and were collected by the Federal Employment Agency (*Bundesanstalt für Arbeit*, BA) for social security purposes.[3] We have an origin-destination (OD) matrix, of dimension 439×439, which contains, for each cell (i, j), the number of employees residing in district i and working in district j (that is, home-to-work trips). We also employ a district classification developed by the Federal Office for Building and Regional Planning (*Bundesanstalt für Bauwesen und Raumordnung*, BBR) (Böltgen and Irmen 1997), regarding levels of urbanization and agglomeration, which distinguishes West and East German districts 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 order to show the propensity to mobility of the districts, we employ indicators of incoming and outgoing mobility, which we refer to, adapting from Van der Laan (1998), as inward and outward "openness." The inward openness of a district indicates to what extent it attracts workers from outside, and is computed as the percentage of local jobs absorbed by outside workers.[4] Similarly, the outward openness can be defined as the percentage of resident workers who commute outside of their district. Figure 1 and Figure 2 present a visualization of the change of district inward and outward openness, respectively, within Germany between 1995 and 2005.

Concerning inward mobility, for both 1995 and 2005, greater inward openness is observed for the central cities (types 1 or 5). These are overrepresented among the most open districts. While districts of type 1 or 5 are only 72 out of 439 (16% of the total), they account for 46 percent of the districts with an inward openness greater than 0.50. Therefore, central cities appear to truly function as small regional open systems. This result could be accentuated by the limited area of such districts. In fact, the German *kreise* (NUTS-3) classification has rather

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[3] Since the data were directly gathered at the level of individual firms, it is reasonable to expect low and non-systematic measurement errors.

[4] The inward openness is computed, for a 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 the district. If e_{ij} is the number of individuals living in i and working in j, the inward openness of district j is equal to: $\sum_{i \neq j} e_{ij} / \sum_i e_{ij}$. Similarly, the outward openness of district i is equal to: $\sum_{j \neq i} e_{ij} / \sum_j e_{ij}$.
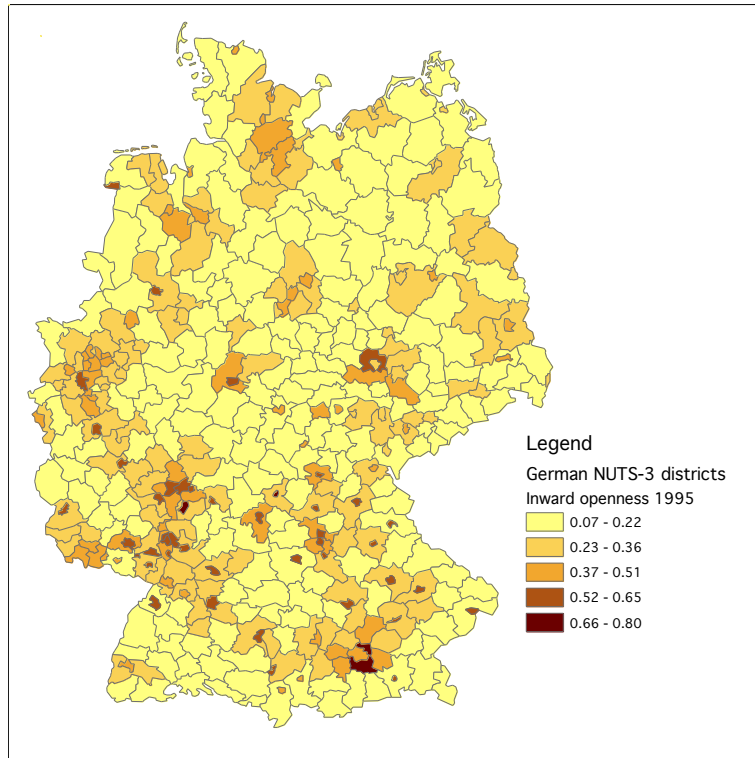
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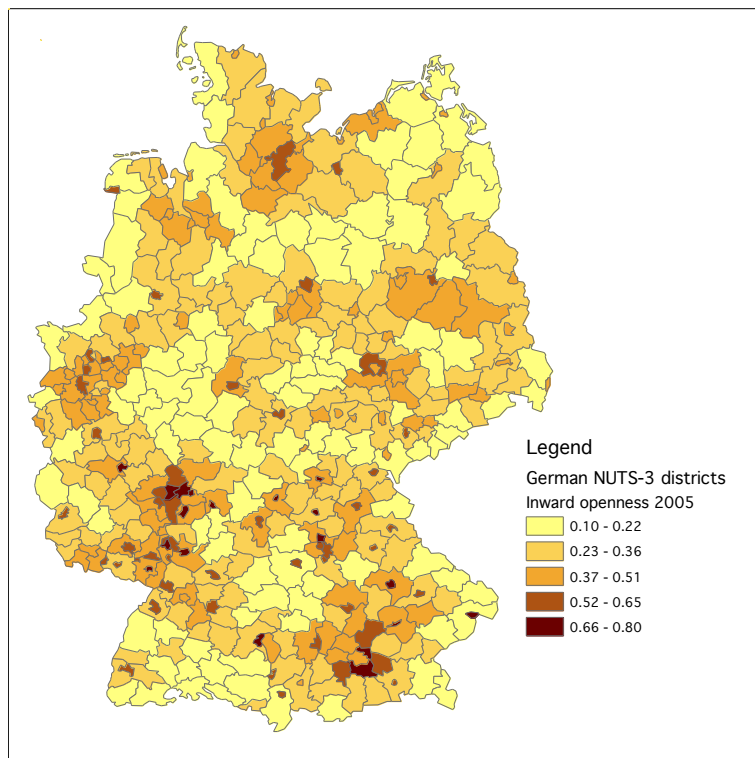
(b) 2005

Figure 1: Maps of inward openness per district, 1995 and 2005.

small districts for the main cities, whereas larger districts surround them (for example, districts of type 2). These findings are consistent with conventional approaches in regional and urban economics and in spatial interaction modeling. Overall, though not a central city, the district of type 2 surrounding Munich (*Landkreis München*) emerges as the most open (inwards), as workers residing outside the district take up 70 percent (1995) to 76 (2005) percent of the local jobs considered. As seen from these shares, the trend is towards a further accentuation of this peculiarity. Berlin, however, represents a unique case: because of its economic significance and large population, the city generates large flows (in absolute terms) both inwards and outwards; but, on the other hand, Berlin has rather low inward openness (11% in 1995, 20% in 2005).

As far as the evolution of the indicators is concerned, a general increase in mobility is evident over the ten years of the data set. In particular, the area surrounding Berlin seems to attract a larger share of commuters in 2005 than in 1995. As the first year of our data set (1995) is only a few years after the German reunification, we might consider the higher propensity to mobility in 2005 to be the result of the reintegration of Berlin as the capital of Germany, from which a number of positive economic (economic/employment) externalities can be assumed[5] (e.g. Burda and Hunt 2001).

The evolution of openness can also be seen in Table 1, which shows the openness of the nine types of districts. The overall dominance of the central city districts as regional mobility poles is also exemplified here. Central cities (of types 1 and 5) appear to have great inward mobility (ranging from 37% to 53% in 1995 and 2005, respectively) compared with their surrounding districts of types 6 and 2 (22–37%). This hierarchy is reversed when considering outgoing commuters. Highly urbanized districts (of type 2) show the greatest share of commuters leaving their districts for work (39% and 45% in 1995 and 2005, respectively), followed by the urbanized districts of type 3 (38% in 1995 to 45% in 2005). In summary, the central cities show a "pull" effect, while the urbanized districts display a "push" effect (see also Figures 1 and 2), in agreement with the transport economic generation/attraction models. The remaining district types show intermediate values, within a general increase over the years in the levels of mobility.

After observing the distribution of inward and outward openness, we can use the average of the two indicators as a measure of the overall openness of the districts. This synthetic openness measure represents the capacity of a district to be mobile and, consequently, active. Van der Laan (1998, 238) identifies high values of openness as possible signs of a "multi-nodal urban region."

In Figure 3, which maps the openness values, a specific group of cities emerges as the most active in both years. These are mainly central cities (of type 1) and highly urbanized districts (of type 2), with the Munich *Landkreis* appearing as the most open in both 1995 and 2005. This finding might be explained by these areas' greater concentrations of population and economic activity (located within the city itself, or in its environs), or even by the characteristics of a mobile population exploring new opportunities instead of conventional jobs (Van Oort 2002). Exceptions with rather low openness values, such as Berlin and the city district of Munich (an entity separate from the surrounding *Landkreis*), should be noted. The reason for these exceptions should be sought in the fact that the districts to which these cities belong are larger than other central city districts, but still have a high population density. Consequently, commuting (for example, from the city periphery to the central business district) seems to be carried out within the district boundaries. Over the 10-year period we observe a generalized increase in

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[5] The German parliament and government restarted operations in Berlin in 1999.
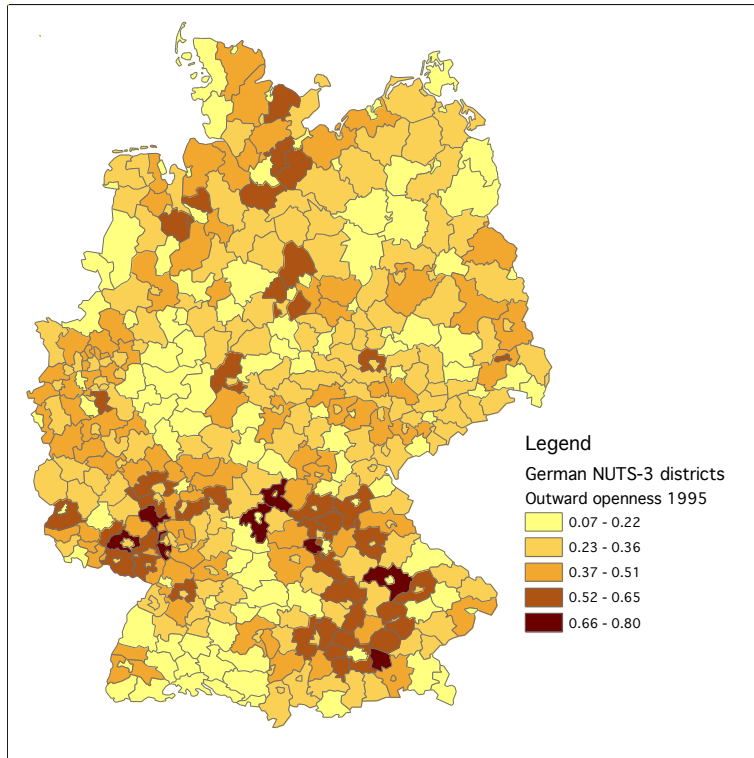
(a) 1995
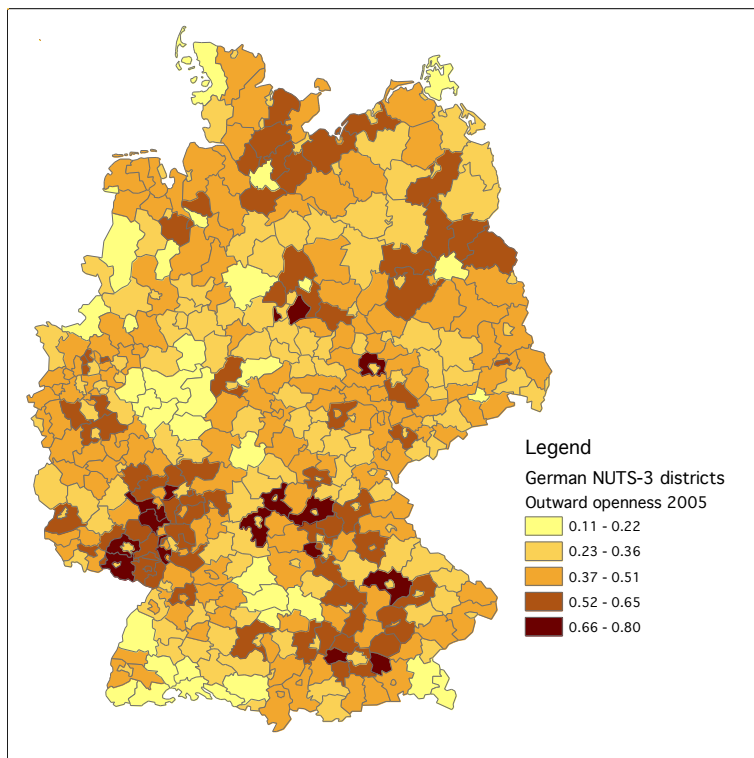
(b) 2005

Figure 2: Maps of outward openness per district, 1995 and 2005.

**Table 1:** Inward, outward, and total openness by type of district urbanization.

| District Urbanization*	Inward		Outward		Openness	
	1995	2005	1995	2005	1995	2005
Type 1: Central cities in regions with urban agglomerations	37.4	45.6	20.1	27.4	28.8	36.5
Type 5: Central cities in regions with tendencies towards agglomeration	44.2	53.3	22.2	30.0	33.2	41.7
Type 2: Highly urbanized districts in regions with urban agglomerations	29.9	37.4	38.7	44.6	34.3	41.0
Type 6: Highly urbanized districts in regions with tendencies towards agglomeration	22.4	28.2	33.6	40.0	28.0	34.1
Type 3: Urbanized districts in regions with urban agglomerations	25.1	32.5	38.2	45.2	31.6	38.9
Type 8: Urbanized districts in regions with rural features	27.0	33.9	30.0	36.8	28.5	35.4
Type 4: Rural districts in regions with urban agglomerations	23.1	31.5	37.4	48.7	30.3	40.1
Type 7: Rural districts in regions with tendencies towards agglomeration	18.9	24.7	29.3	36.8	24.1	30.7
Type 9: Rural districts in regions with rural features	18.1	23.9	25.9	33.1	22.0	28.5
Totals	29.8	37.1	29.8	37.1	29.8	37.1

* See Böltgen and Irmen (1997).

the propensity to mobility, while a more-than-proportional variation can be found for the area surrounding Berlin. In this context, it could be interesting to explore whether the most open cities identified 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 patterns are affected by the underlying connectivity networks, taking into account the findings on multi-nodality[6] presented by Van Nuffel and Saey (2005) for the case of the Flanders region, and by Batten (1995) for the Netherlands and Japan. This issue is investigated in the next section.

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[6] Van Nuffel and Saey (2005) find indications of multi-nodality (defined as van der Laan's integration of commuting systems with a high intensity of local non-nodal relations) for the area of Ghent-Hasselt. Batten (1995) discusses the existence of network cities, of which local and regional multi-nodality (Van Nuffel and Saey 2005) can be considered as special cases.
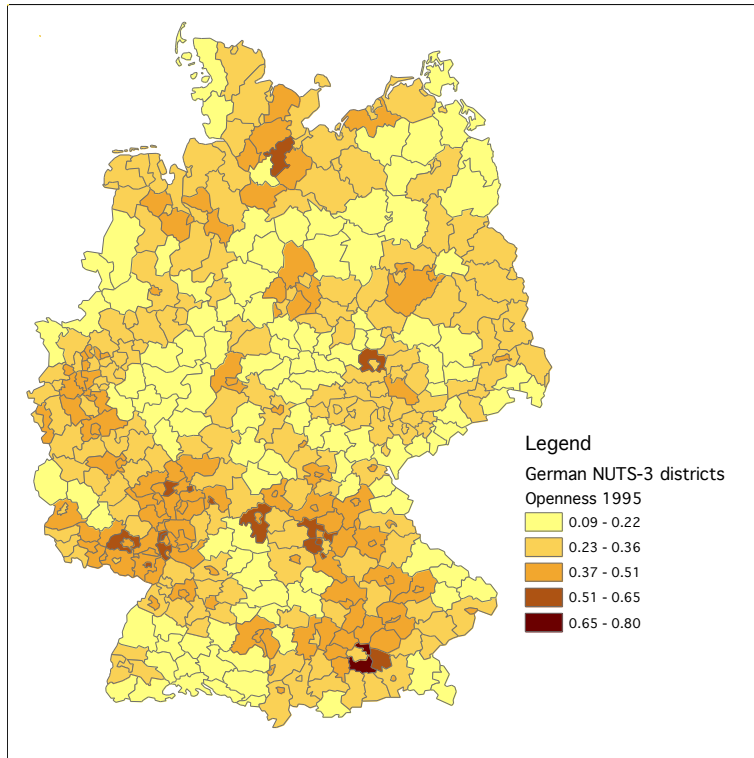
(a) 1995
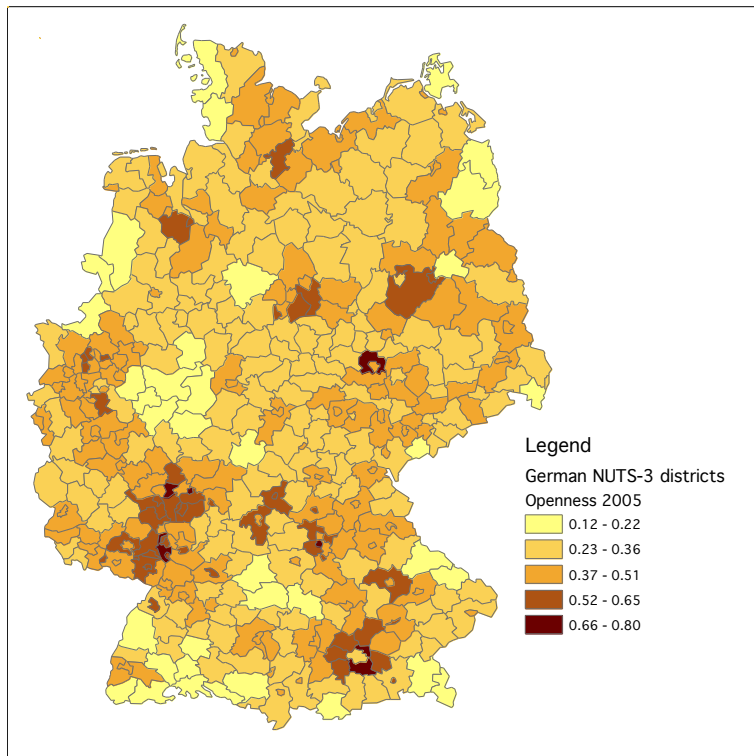
(b) 2005

Figure 3: Maps of openness of districts, 1995 and 2005.

4 Dynamics of Commuting: Network Data Exploration

4.1 Preface

The following sections present a set of network connectivity analyses investigating the distributional properties of German commuting. Section 4.2 aims to show how incoming and outgoing flows per district, and district-to-district connections, are allocated over the country. Subsequently, Section 4.3 presents aggregate indices concerning the commuting network, while indicating its levels of centralization (dispersion) and interconnectivity.

4.2 Connectivity

An initial analysis of the network underlying the commuting activities can be carried out by considering the statistical distribution of the mobility observed between districts. We deal with inward and outward commuting separately, in order to identify the attractiveness (inward commuting) and propensity to mobility (outward commuting) of the districts. Two exploratory approaches are adopted here. First, following the formulation of Zipf's law in Equation (2), the number of inward connections per district (referred to hereafter as "indegree"; de Nooy *et al.* 2005) is examined—that is, from how many districts do commuters come. From this perspective, any commuting between two districts i and j is relevant, regardless of its extent; we are therefore looking at logical topology.[7] Secondly, we examine the inward openness of the districts (as defined in Section 3). This approach considers the weights of the links—that is, the inflows. In detail, the total inflows of each district are standardized by the number of jobs available there. The distributions of incoming connections and inward openness, for 1995 and 2005, are plotted in Figures A-1 and A-2 in the Appendix.

We next interpolate the related data for 1995 and 2005 with two types of nonlinear functions: a power and an exponential function (see Section 2, Equations (2) and (4)). The resulting R^2 coefficients, as well as the values of the exponents of the functions, are shown in Table 2. For the case of the indegree distribution (incoming connections per district), an exponential distribution fits the degree decay rather well, with the exception of a sharp cut-off at the end. The R^2 for the exponential function decreases slightly over time, from 0.97 to 0.93. The R^2 for the power function is lower (around 0.70) and also decreases over time (to approximately 0.60). If we follow Adamic's suggestion and transform the indegree power-law coefficient according to Equation (3), we obtain coefficients much greater than 3, suggesting that the commuting network possesses characteristics of a random network (homogeneous pattern).[8] Overall, these findings suggest that the commuting network is highly interconnected, with few districts that can be considered more peripheral in network terms. However, given the ambiguity of these results with respect to exponential and power-law characteristics, no clear agglomeration pattern can be inferred in the case of indegree distribution.

As in the case of indegree distribution, the results for the distribution of inward openness in the two years remain fairly stable. As observed for indegree distribution, the exponential

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[7] Logical topology is the (virtual) network configuration emerging from the OD matrix; by contrast, physical topology concerns the (real) physical infrastructure of the network.

[8] It should be noted that these results would vary if we imposed a minimum threshold on the flows associated with each link. We would already see relevant differences if we chose to set this threshold at 3 (that is, not considering links with flows under 3): the power-law coefficient (now between 2 and 3) would suggest that the commuting network possesses SF characteristics.

Table 2: 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)

function better interpolates the data (the R^2 being 0.99); however, the power function also has a high R^2 of 0.78–0.80. In addition, the exponent values for the power interpolation are now higher (0.40–0.46). In this case also, the transformed power-law coefficients are greater than 3. Overall, this preliminary data exploration shows that the exponential function is a better fit to both the indegree and the inward-openness distributions, suggesting an equilibrated network for these variables. These results with regard to the indegree coefficients could be attributed to the lack of network growth and rewiring, two critical factors that drive the emergence of scale-free properties in networks. On the other hand, the results for the inward-openness distribution could be attributed to the constrained values assumed by the variable analyzed (between 0 and 1) after standardization. The results for the non-standardized inflow values can be found in Table 5, Section 5.2.

4.3   Network Indices

After exploring the data and their distribution, we provide a set of synthetic indices, which describe three principal aspects in order to explore the network under different perspectives: (a) centralization; (b) clustering; and (c) variety/dispersion. The first of these indices, network centralization, is an assessment of the degree of inequality (or variance) in a network. It may be computed on the basis of individual node centrality measures. In this regard, the centrality of a node can be defined as a measure of its structural importance (the relative importance of a node within a graph). Various centrality indicators have been developed over the years (e.g. Freeman 1977; Sabidussi 1966), which take into consideration different concepts of centrality. The centrality indicator presented here, when applied to the entire network, may be called "indegree centralization," and is based on the concept of the relative degree centrality of nodes. This measure deals with the "visibility" of a node—in the present case, a district. Visibility can be linked to the hub concept (Latora and Marchiori 2004), since the most visible node can be considered as a hub. The distinctive feature of this index, compared with other indices described in the literature, is that it only considers direct connections (indirect connections cannot be considered in our case study of commuting, unless the transportation infrastructure is included in the analysis). In the present application, only inward connections are considered (hence, the denomination "indegree centralization"), in order to show the nodes' attractiveness for outside workers. The indegree of a node is seen, in social network analysis, as a measure of prestige. In this case, it can be considered as a dominance index. 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 $(N1)$, where N is the total number of nodes:

$$\text{ric}_i = \frac{\text{indegree}_i}{(N-1)},$$
(5)

while the aggregate network indegree centralization (NIC) index is computed, following Freeman (1979), as:

$$\text{NIC} = \frac{\sum_{i \in N}(\text{ric}^* - \text{ric}_i)}{(N-2)},$$
(6)

where ric^* is $\max_i(\text{ric}_i)$.

The second index computed refers to network clustering. Network clustering coefficients have been used extensively in network analysis, for instance to search for small-world networks (see Watts and Strogatz 1998). We consider clustering coefficients in order to determine the level of interconnectedness of the network. In order to compute a clustering coefficient for a node, we need to define its neighborhood. Neighbors are identified (if first-order relations are considered) as the nodes directly connected to the node concerned. Consequently, a first-order clustering coefficient for node i is computed as the ratio of the number of links existing between the nodes of its neighbors and the maximum number of links that may exist between the same nodes:

$$c_i = \frac{l_i}{l_i^*},$$
(7)

where l_i and l_i^* are the actual and possible number of links, respectively, in the neighborhood of node i. In a fully connected network (where each node is connected to each of the other nodes) all nodes will have a clustering coefficient of 1. A synthetic network clustering coefficient is then computed as the average of the single nodes' coefficients. If k-order neighbors are considered, a node's neighborhood is represented by all the nodes that can be reached in k hops, and a k-order clustering coefficient will consequently be computed. In this latter case, the observation of a high level of clustering suggests a highly interconnected network.

We use the entropy formulation as a final index to describe the network's connectivity from the perspective of the variety/dispersal of centers. Entropy is a concept originally derived from information theory (Shannon 1948) and widely used in spatial-economic science, thanks to Wilson (1967, 1970) statistical studies. Entropy has recently been applied by several authors in order to identify hidden order in urban sprawl (Sun *et al.* 2007), in urban traffic (Haynes *et al.* 2006), and in industrial economics (Frenken 2006). In our context, entropy is employed as an indicator of the probability that the flows observed are generated by a stochastic spatial allocation process (Nijkamp and Reggiani 1992, 18). The higher the entropy, the more dispersed the flows are over the network. The indicator is computed as:

$$E = -\sum_{ij} p_{ij} \ln p_{ij},$$
(8)

where:

$$p_{ij} = \frac{t_{ij}}{O_i}.$$
(9)

In Equation (9), t_{ij} is the number of commuters between districts i and j, while O_i represents the outflows of district i.

The results computed for the German commuting network, according to the three indices described above, are presented in Table 3. Years 1995 and 2005 are again taken into consideration. Although no dramatic changes seem to occur over the ten years, the network shows two distinct trends. On the one hand, the centralization of the network decreases (at least as far as inward connections are concerned) and the entropy increases. These results imply that the structure of the network has become more distributed over time. 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), highlighting the network's tendency towards a multi-nodal structure (Van der Laan 1998).

**Table 3:** 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

A graphical representation of the multi-polar tendency in the commuting network structure—in our case, from an inward connections viewpoint—can be obtained, for 1995 and 2005, on the basis of the 'k-core' concept (Figure 4). [9] A k-core consists of one or more subgraphs in which each included node has a minimal degree (in our case, indegree) of k; that is, each node in the k-core has direct connections with at least k other nodes in the same subgraph (Holme 2005). For a more meaningful computation and a readable graph, we have selected a subsample of the data consisting only of those commuting flows above an arbitrary threshold of 1000 individuals. We find k-cores of level 4 (4-cores), comprising 13 and 33 districts for 1995 and 2005, respectively.

For the year 1995, we find a small core of 13 districts that define a heavily interconnected (and local) network dominated by Düsseldorf and Dortmund. Each node (district) appearing in our 4-core receives at least 1000 commuters from at least four other nodes in the same core, showing in this case intense horizontal (local) relations. The fact that other districts do not appear in the 4-core does not mean that they do not have reciprocal flows of commuters with the core districts, merely that these other nodes are not characterized by the minimal levels of interconnectedness and number of commuters of the core nodes—although they may be involved in several district-to-district flows of more than 1000 individuals. Frankfurt is the most evident example; although this city was not included in the 1995 4-core, it appears in the 2005 4-core, which is a larger and denser graph composed of 33 districts. While the Düsseldorf/Dortmund cluster acquires additional nodes and is still the main body of the core, the role of Frankfurt (code 6412) is noteworthy, as it is now included in the 4-core and acts as a hub, connecting a local cluster of its own to the main Düsseldorf/Dortmund cluster. Of course, as these results relate to logical (rather than physical) topology, it is not implied here that Frankfurt physically connects nodes belonging to the two parts of the core cluster.

The results of the network analysis carried out in the present section seem to confirm the multi-nodal structure of the German commuting network (especially at the local level), while

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[9] Core computations were carried out using the freely available software Pajek (http://vlado.fmf.uni-lj.si/pub/networks/pajek/).
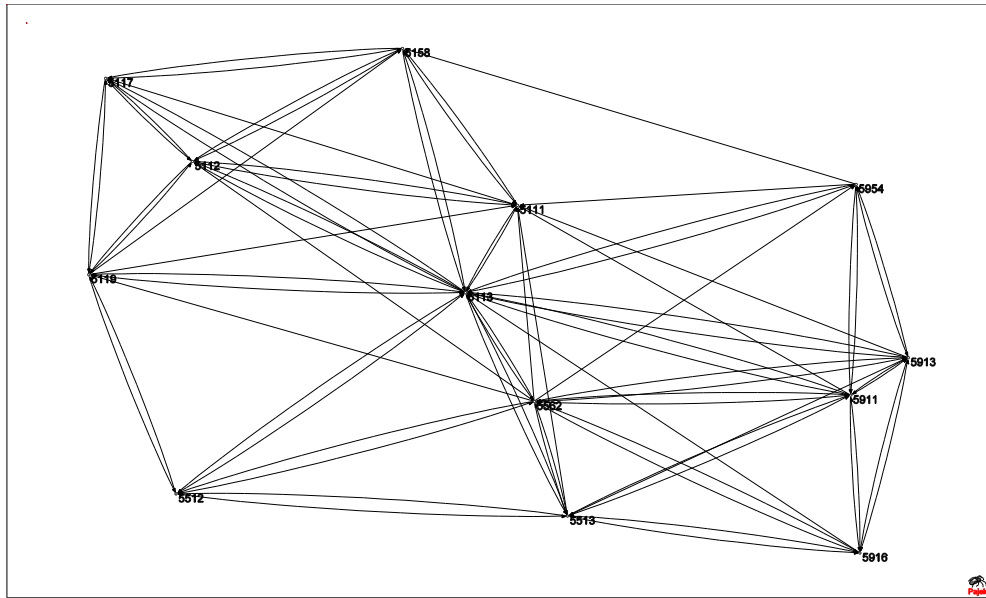
(a) 1995
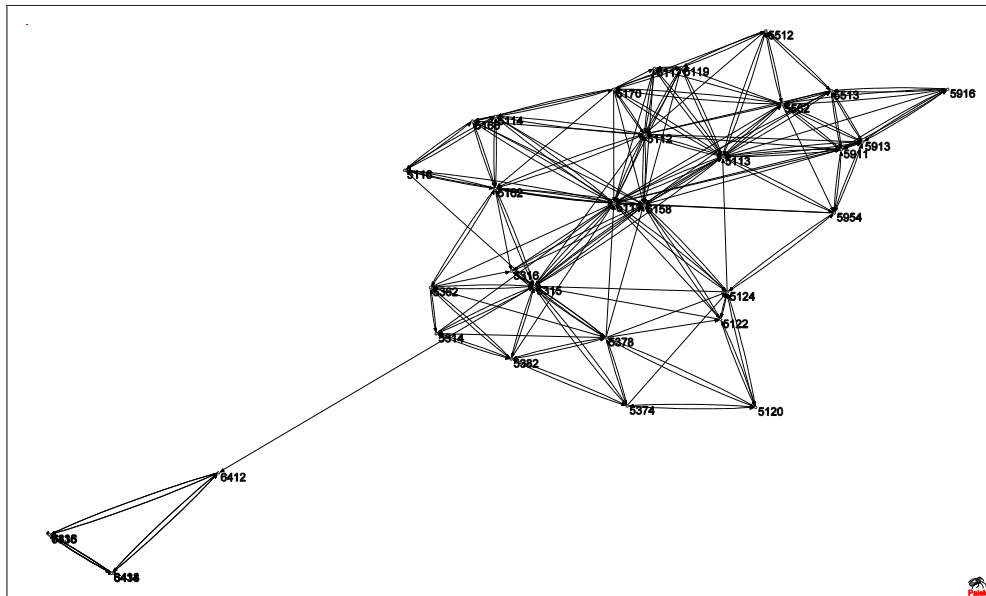
(b) 2005

Figure 4: Logical topology of 4-cores in the commuting network, 1995 and 2005. Codes for the main districts are: 5111 (Düsseldorf); 5112 (Duisburg); 5113 (Essen); 5315 (Cologne); 5158 (Mettmann); 5316 (Leverkusen); 5911 (Bochum); 5913 (Dortmund); 6412 (Frankfurt).

also suggesting that connectivity between the major centers (Berlin, Stuttgart, Munich, and so on) increases over time while centrality decreases. Further, these results suggest a consequent tendency toward two layers of multi-nodality: (a) at the local level (see for example the Düsseldorf/Dortmund cluster); and (b) at the regional (city-network) level. As also observed by Van Nuffel and Saey (2005, p. 326) and by Van der Laan (1998, p. 244), these relations between the main centers do not overshadow local links (which still carry most of the mobility) but complement them.

As a next step of this research endeavor, it is worthwhile to map the hierarchies of the districts and their persistence over time within this multi-nodal structure in order to identify the main relevant centers from both a spatial and a network viewpoint. In order to offer a synthetic measure of the multiple spatial and connectivity dimensions—with reference to the dynamics of the districts under analysis—we use a multidimensional method, well-known in the spatial-economic literature, called multicriteria analysis. This method may serve to identify the most prominent configurations in Germany.

5   Multidimensional Assessment: Application of Multicriteria Analysis

5.1   The Network of "Open" Districts

The present section aims to provide a synthetic assessment of the district characteristics observed in Sections 3 and 4, by means of both a spatial and a connectivity approach, for the purpose of defining a dominance ranking of the main districts concerned. We are also interested in investigating changes in this ranking over the period 1995–2005.

The subsample of districts (alternatives) employed in our multicriteria analysis (MCA) is selected on the basis of a synthetic connections-flows (CF) index, computed as follows for each district i:

$$\text{CF}_i = \left(\frac{C_i}{\max_i(C_i)} \right) \left(\frac{F_i}{\max_i(F_i)} \right). \tag{10}$$

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 it ranges from 0 to 1. This index aims to provide a balanced assessment of the openness and connectedness of the districts, that is, from a conventional spatial interaction perspective and a network perspective, respectively. On the basis of the CF index, we were able to select 26 districts that appear among the top 30 districts for both 1995 and 2005. Such a stable group of open districts (26 of 30) over a 10-year period suggests a generally stable relationship between the upper tier and the rest of the districts. If we consider the district urbanization index shown in Table 1, we find that the districts, with only a few exceptions, are urban districts—central cities of types 1 and 5.

The MCA is carried out on the basis of two aggregate assessment criteria (macro-criteria):[10] spatial mobility (comprising inward and outward openness; see footnote 4) and connectivity (comprising relative indegree centrality and clustering coefficients; see Equations (5) and (7)).

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[10] The regime multicriteria method (and software) was used (Hinloopen and Nijkamp 1990). In particular, three scenarios were considered at all stages: (a) equal weights to all criteria; (b) ascending weights; and (c) descending weights. A further MCA of the resulting rankings provides the final results.

We now proceed in two steps: first, by carrying out an MCA for each macro-criterion (consisting of the individual criteria described above); and, second, by carrying out a final MCA which synthesizes the two previous analyses.[11]

With respect to the MCA based on spatial-economic indicators, the results show that, of the main cities included, Munich (*Landkreis*) persistently occupies the first position (Table 4). Moreover, the ranking of the top districts is rather stable over the two years concerned. It is noteworthy that other prominent cities such as Frankfurt, Stuttgart and Düsseldorf do not perform as well as Munich.

The results of the second MCA, based on connectivity criteria, provide a rather different ranking for 1995, in which the main cities are dominant. As seen in Section 4 for the k-core results, Düsseldorf emerges as important from a network perspective. Other large cities such as Frankfurt, Stuttgart and Munich follow. It is interesting to observe that in 2005 some centers attain higher rankings, most notably Wiesbaden (a district in the Frankfurt metropolitan area and capital of the state of Hesse) and Karlsruhe. We can also note that, with the exception of Munich, the districts that headed the spatial MCA rankings only perform at an intermediate level in the connectivity MCA.

The final results, which synthesize the two preceding analyses by employing the results of the spatial and connectivity macro-criteria, can be summarized as follows. The district of Munich (*Landkreis*) emerges as the most dominant for both 1995 and 2005, while a reshuffling in the ranking of the districts can be observed over the 10-year period. Some dynamic districts seem to emerge, particularly 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 observed progress of such districts is mainly due to the connectivity macro-criterion. Their high clustering coefficients show that these districts are not only open, but oriented towards agglomeration patterns.

The districts emerging in the above analysis are the most open and active, but they still cannot be considered as the main "attractors." If we want to explore this characteristic, we then have to use other variables that can detect the relevance of the destination (such as actual inflows or workplaces) in the CF index computation of Equation (10), as the well-known attraction models in transport literature suggest. The result of this further analysis (again utilizing MCA) is illustrated in next section.

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[11] We assume, in our analysis, the hypothesis of absent correlation between the criteria employed in the MCA. In this context, a foreseeable endeavor is investigating possible correlations between the criteria.

Table 4: The network of "open" districts: Rankings resulting from multicriteria analysis of openness and connectivity criteria for 1995 and 2005.

	Spatial results[a]			Connectivity results[b]			Final results[c]	
District	1995	2005	District	1995	2005	District	1995	2005
09184 Munich	1	1	05111 Düsseldorf (St)	1	1	09184 Munich	1	1
06436 Main-Taunus-Kreis	2	2	06412 Frankfurt am Main (St)	2	2	06436 Main-Taunus-Kreis	2	4
09661 Aschaffenburg (St)	3	4	08111 Stuttgart	3	4	06411 Darmstadt (St)	3	3
06413 Offenbach am Main (St)	4	3	09184 Munich	4	7	07315 Mainz (St)	4	5
06411 Darmstadt (St)	5	5	09564 Nuremberg (St)	5	8	08221 Heidelberg	5	9
07314 Ludwigshafen am Rhein (St)	6	6	05314 Bonn (St)	6	9	05314 Bonn (St)	6	7
08221 Heidelberg	7	8	08222 Mannheim	7	6	06414 Wiesbaden (Lkr)	7	2
07315 Mainz, (St)	8	7	06414 Wiesbaden (Lkr)	8	3	09562 Erlangen (St)	8	15
09662 Schweinfurt (St)	9	15	06436 Main-Taunus-Kreis	9	11	08121 Heilbronn	9	16

(St) = Stadt; (Lkr) = Landkreis
[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.

District	Spatial results[a]		District	Connectivity results[b]		District	Final results[c]	
	1995	2005		1995	2005		1995	2005
08121 Heilbronn	10	9	08212 Karlsruhe	10	5	07314 Ludwigshafen am Rhein (St)	10	18
09461 Bamberg (St)	11	12	06411 Darmstadt (St)	11	10	08421 Ulm	11	12
08421 Ulm	12	11	07315 Mainz (St)	12	13	06412 Frankfurt am Main (St)	12	8
09562 Erlangen (St)	13	10	09562 Erlangen (St)	13	12	06413 Offenbach am Main (St)	13	10
06611 Kassel (St)	14	16	08221 Heidelberg	14	15	08222 Mannheim	14	6
07111 Koblenz (St)	15	13	08421 Ulm	15	14	08111 Stuttgart	15	11
06414 Wiesbaden (Lkr)	16	14	08121 Heilbronn	16	20	06611 Kassel (St)	16	17
05314 Bonn (St)	17	17	09663 Wuerzburg (St)	17	22	09661 Aschaffenburg (St)	17	20
09362 Regensburg (St)	18	20	07314 Ludwigshafen am Rhein (St)	18	21	05111 Düsseldorf (St)	18	13

(St) = Stadt; (Lkr) = Landkreis
[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.

	Spatial results[a]			Connectivity results[b]			Final results[c]	
District	1995	2005	District	1995	2005	District	1995	2005
09161 Ingolstadt (St)	19	24	06413 Offenbach am Main (St)	19	16	09663 Wuerzburg (St)	19	24
09663 Wuerzburg (St)	20	19	06611 Kassel (St)	20	17	07111 Koblenz (St)	20	22
08222 Mannheim	21	18	09161 Ingolstadt (St)	21	18	08212 Karlsruhe	21	14
06412 Frankfurt am Main (St)	22	22	09362 Regensburg (St)	22	19	09564 Nuremberg (St)	22	19
08111 Stuttgart	23	21	07111 Koblenz (St)	23	24	09461 Bamberg (St)	23	25
05111 Düsseldorf (St)	24	25	09661 Aschaffenburg (St)	24	23	09161 Ingolstadt (St)	24	23
08212 Karlsruhe	25	26	09461 Bamberg (St)	25	25	09362 Regensburg (St)	25	21
09564 Nuremberg (St)	26	23	09662 Schweinfurt (St)	26	26	09662 Schweinfurt (St)	26	26

(St) = Stadt; (Lkr) = Landkreis
[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.

Table 5: R^2 values and exponents for power and exponential interpolations of incoming connections (indegree) and inflows, 1995 and 2005.

Year	Indegree		Inflows	
	Power law	Exponential	Power law	Exponential
1995	0.7002	0.9739	0.9447	0.9163
(exponent)	(0.2442)	(0.0022)	(0.8962)	(0.0068)
2005	0.6046	0.9316	0.9411	0.9162
(exponent)	(0.2589)	(0.0025)	(0.8841)	(0.0067)

5.2 The Network of "Attractive" Districts

The preceding section illustrated the results for the MCA that investigated the group of the most open and connected districts. However, in the light of the transport economics literature, this group of cities cannot be identified as the most attractive ones (and hence, according to Barabási's work, the "preferential nodes" or hubs). On the basis of the attraction model formulation in the conventional four-step transportation model, the attraction variable is conventionally identified as the total inflows per district (or another variable that represents the relevance of destinations, such as workplaces). We therefore repeat our last analysis, replacing the inward openness index previously employed in calculating the CF index with the total inflows per district, which can be seen as a measure of the importance of destinations.

As inflows are not normalized by city size, they have a different distribution with respect to the inward openness, the characteristics of which are reported in Table 5 and plotted in Figure A-3 in the Appendix. While the distribution of the inward openness largely fits an exponential function (see Section 4.2), the distribution of the inflows according to Equation (2) is best interpolated, in this case, by the power function (an R^2 of 0.94, compared to 0.92 for the exponential case). Also, the value of the power function exponent of approximately 0.89 is more interesting than the value of 0.46 observed for inward openness (see Table 2). In fact, the transformed coefficient would be approximately 2.1, which suggests the emergence of hub patterns (in particular, Munich, Frankfurt and Hamburg seem to emerge as principal attraction-hub nodes).

Having observed the variation in the distributional results obtained by employing inflows, we modify the CF index (see Equation (10)) so as to include total inflows in place of inward openness. Employing the same selection process illustrated above, we then obtain a new group of 29 districts to be analyzed as alternatives in a further MCA. The same methodology followed in the preceding section applies. This new group is evaluated by means of the same criteria employed in Section 5.1 in order to classify the attraction districts on the basis of their openness and connectedness. The results of the spatial and connectivity MCAs, as well as the final MCA results, are summarized in Table 6, showing a hierarchy of attraction nodes which are also open and active.

In this concluding analysis, Munich (*Landkreis*) again emerges at the top of the rankings for the spatial MCA. The connectivity MCA instead favors the main German cities, such as Hamburg, the Düsseldorf/Cologne agglomeration, and Frankfurt, with Munich and Berlin following closely. The results from the final MCA, a synthesis of the two preceding MCAs,

show that the 1995 hierarchy (which, in principle, represents the main German cities) changes in 2005 because of the emergence of new districts such as Mettmann (which moves from 5th position to 1st), Weisbaden (9th to 2nd), Darmstadt (16th to 8th), and Karlsruhe (15th to 9th). As a consequence, the main cities fall in the ranking; the most notable examples are Munich (from 1st to 3rd), Frankfurt (2nd to 5th), Stuttgart (3rd to 4th), and Düsseldorf (4th to 6th). Once again, this reshuffling can mostly be attributed to the high clustering coefficient values attached to the emerging districts.

The finding of an evolution over time suggests the possibility of a reinterpretation (or expansion), in the economic sense, of the concept of the network hub described by Barabási et al. This new concept of the hub should be based not only on a node's capacity to attract connections from many other nodes, but also on its capacity to generate an increased propensity to mobility toward different nodes.

The selection of the 29 districts analyzed emerges from the choice of the inflows variable in the CF index, as an indicator for the attraction nodes (Equation (10)). If, on the other hand, we wish to consider in this index the strength of the connection (in other words, inflows and outflows, by means of, for example, spatial interaction models) instead of the attraction only (the inflows), we may expect to be more likely to detect the hub cluster, since a hub (in a strict sense) not only attracts flows, but also distributes them (hub-and-spoke).[12]

6   Conclusions

This paper has presented a dual analysis of commuting trends in Germany, from both a spatial and a network perspective. We have analyzed data for home-to-work trips for 439 German districts for the years 1995 and 2005.

With regard to the spatial perspective, we considered the distribution of commuting inflows and outflows per district, in our case normalized by jobs and residents, respectively (Section 3). Our analyses showed that, as expected, mobility revolves around the major metropolitan areas, and that the districts identified as central cities (of types 1 and 5; see Section 3) have the larger shares of inward labor mobility. When considering inward and outward mobility in a synthetic indicator (openness), the *Landkreis* of Munich (an independent district surrounding the city itself) emerges as the most mobile center, most likely because it encompasses the city.

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[12] In this context, it can be shown that, had inflows and outflows been employed as criteria for the spatial MCA, a ranking similar to the one of the connectivity MCA would have emerged.

Table 6: The network of "attractive" districts: Rankings resulting from multicriteria analysis of the openness and connectivity criteria, 1995 and 2005.

District	Spatial results[a]		District	Connectivity results[b]		District	Final results[c]	
	1995	2005		1995	2005		1995	2005
09184 Munich	1	1	02000 Hamburg, Freie und Hansestadt	1	1	09184 Munich	1	3
06411 Darmstadt (St)	2	2	03241 Region Hannover	2	15	06412 Frankfurt am Main (St)	2	5
07314 Ludwigshafen am Rhein (St)	3	3	05111 Düsseldorf (St)	3	2	08111 Stuttgart, (Lkr)	3	4
07315 Mainz (St)	4	4	05315 Cologne (St)	4	4	05111 Düsseldorf (St)	4	6
05158 Mettmann	5	5	06412 Frankfurt am Main (St)	5	5	05158 Mettmann	5	1
06414 Wiesbaden (Lkr)	6	6	08111 Stuttgart (Lkr)	6	7	08222 Mannheim, Universitätsstadt	6	7
05314 Bonn (St)	7	7	09162 Munich (St)	7	11	05314 Bonn (St)	7	10

(St) = Stadt; (Lkr) = Landkreis
[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.

District	Spatial results[a]		District	Connectivity results[b]		District	Final results[c]	
	1995	2005		1995	2005		1995	2005
08222 Mannheim, Universitätsstadt	8	8	11000 Berlin	8	14	09564 Nuremberg (St)	8	14
05911 Bochum (St)	9	11	08116 Esslingen	9	16	06414 Wiesbaden (Lkr)	9	2
08111 Stuttgart (Lkr)	10	10	09184 Munich	10	12	05315 Cologne (St)	10	12
06412 Frankfurt am Main (St)	11	12	09564 Nuremberg (St)	11	13	08116 Esslingen	11	16
05112 Duisburg (St)	12	9	14365 Leipzig (St)	12	26	05113 Essen (St)	12	19
09761 Augsburg (St)	13	13	14262 Dresden (St)	13	28	07315 Mainz (St)	13	18
05111 Düsseldorf (St)	14	14	04011 Bremen (St)	14	20	09162 Munich (St)	14	17
05113 Essen (St)	15	15	08222 Mannheim, Universitätsstadt	15	10	08212 Karlsruhe (St)	15	9
08212 Karlsruhe (St)	16	16	05158 Mettmann	16	3	06411 Darmstadt (St)	16	8
08115 Böblingen	17	17	05314 Bonn (St)	17	17	09761 Augsburg (St)	17	13

(St) = Stadt; (Lkr) = Landkreis
[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.

	Spatial results[a]			Connectivity results[b]			Final results[c]	
District	1995	2005	District	1995	2005	District	1995	2005
09564 Nuremberg (St)	18	19	06414 Wiesbaden (Lkr)	18	6	02000 Hamburg, Freie und Hansestadt	18	20
05913 Dortmund (St)	19	18	05113 Essen (St)	19	22	08115 Böblingen	19	11
05515 Munster (St)	20	22	08212 Karlsruhe (St)	20	9	04011 Bremen (St)	20	25
08116 Esslingen	21	20	08115 Böblingen	21	8	14365 Leipzig (St)	21	28
05315 Cologne (St)	22	21	05913 Dortmund (St)	22	21	03241 Region Hannover	22	24
09162 Munich (St)	23	23	09761 Augsburg (St)	23	19	05911 Bochum (St)	23	21
04011 Bremen (St)	24	26	07315 Mainz (St)	24	25	05112 Duisburg (St)	24	15
14365 Leipzig (St)	25	24	06411 Darmstadt (St)	25	18	05913 Dortmund (St)	25	22
14262 Dresden (St)	26	25	05112 Duisburg (St)	26	23	14262 Dresden (St)	26	29
02000 Hamburg, Freie und Hansestadt	27	27	05911 Bochum (St)	27	24	07314 Ludwigshafen am Rhein (St)	27	23

(St) = Stadt; (Lkr) = Landkreis
[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.

District	Spatial results[a]		District	Connectivity results[b]		District	Final results[c]	
	1995	2005		1995	2005		1995	2005
03241 Region Hannover	28	28	05515 Munster (St)	28	27	11000 Berlin	28	27
11000 Berlin	29	29	07314 Ludwigshafen am Rhein (St)	29	29	05515 Munster (St)	29	26

(St) = Stadt; (Lkr) = Landkreis
[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 regard to the network perspective, we have considered first the distribution of the inward openness and of the number of incoming connections (the indegree) per district (Section 4.2). Our results show that the distribution of the districts' inward openness is slightly more heterogeneous than the indegree distribution. In addition, further heterogeneity is found when the distribution of inflows is considered, implying the possible existence of hub patterns. We have then computed aggregate indicators showing the evolution of the commuting network (Section 4.3); a notable finding from this analysis is that, in addition to a local multi-nodal commuting network (between nearby cities), a regional network is also present to some extent—which, however, does not overshadow well-defined local relations (see, for example, the results of the k-core analysis).[13]

Accordingly, the MCAs carried out in Section 5 suggest that over the 10-year period examined, the hierarchical relationships between German districts are rather stable at the spatial level. In particular, the Munich *Landkreis* emerges as the most mobile and connected district over the study period. In addition, we note (based on the results of the connectivity-focused MCAs) that network connectivity appears to be influenced by the clustering coefficient indicator, as suggested in the works of Watts and Strogatz (1998). In this context, new districts such as Mettmann and Wiesbaden seem to emerge (together with Munich) as the most attractive, open, and connected. This final result mainly depends on the values of the clustering coefficients—which emphasize network agglomerations related to the main dominant districts—in the connectivity criteria; for example, Mettmann is connected to Düsseldorf, and Wiesbaden to Frankfurt. This hub clustering effect might also be taken into account in future research concerned with the identification of network hubs, since they appear to drive the formation of new cluster agglomerations.

Future research into commuting travel demand should address, from a theoretical viewpoint, the behavioral and economic implications of our findings (in particular with regard to the role of distance/travel time and accessibility; wasteful commuting could be an issue) as well as the effects of labor market characteristics. Further, the direction of causality between the regional labor market trends and the network characteristics observed here merits investigation. Finally, efforts should be made to achieve a better understanding of the relationship between the spatial economy and the network characteristics (random, scale-free, and so on) induced by interactions with the economy. In this regard, it is desirable to develop a unique methodological framework rigorously incorporating both spatial and network methodologies.

From a methodological standpoint, a joint analysis of network flows and physical infrastructure is desirable, in order to investigate other topological characteristics such as betweenness-based node centrality. From an empirical standpoint, the study of pre- and post-unification networks in Germany might provide relevant information on the evolution of its commuting patterns. Finally, it would be useful to experiment with alternative spatial disaggregation levels (for example, community levels or functional areas), in order to analyze the consistency of our findings.

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[13] If, in addition to finding high clustering, well-connected nodes are also found to be connected to each other, then highly interconnected clusters can emerge, which, according to Holme (2005), may produce a core-periphery network structure (Chung and Lu 2002). In particular, Holme finds that transportation networks (or, more generically, geographically embedded networks) show these characteristics at some level.

Acknowledgments

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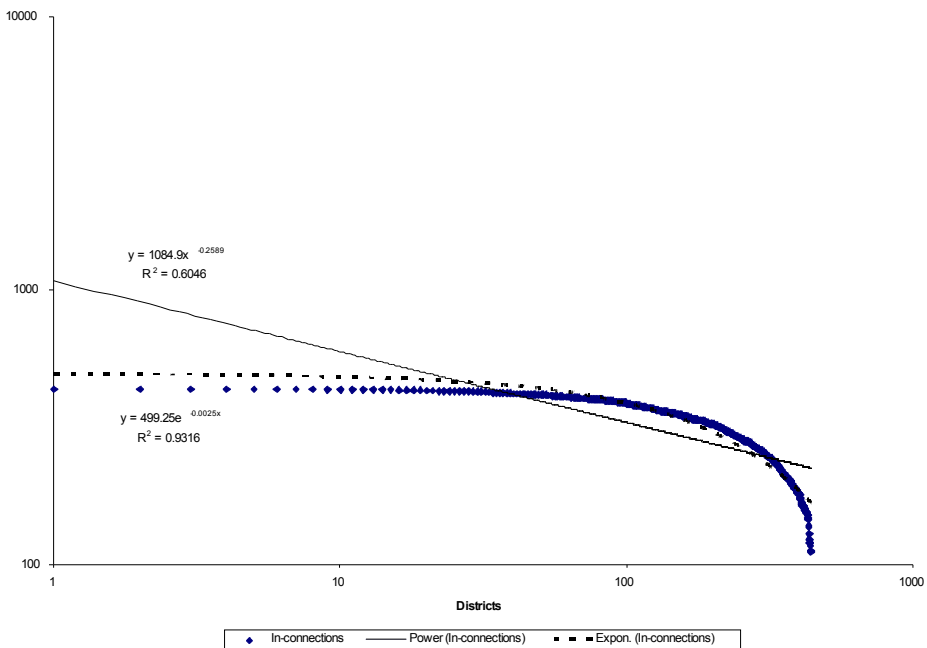Freeman, L. C. 1977. A set of measures of centrality based on betweenness. *Sociometry*, 40:35–41.

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Appendix

$$y = 982.3x^{-0.2442}$$
$$R^2 = 0.7002$$

$$y = 460.55e^{-0.0022x}$$
$$R^2 = 0.9739$$

Districts

In-connections ◆   Power (In-connections) ——   Expon. (In-connections) ▪ ▪ ▪

(a) 1995

$$y = 1084.9x^{-0.2589}$$
$$R^2 = 0.6046$$

$$y = 499.25e^{-0.0025x}$$
$$R^2 = 0.9316$$

Districts

In-connections ◆   Power (In-connections) ——   Expon. (In-connections) ▪ ▪ ▪
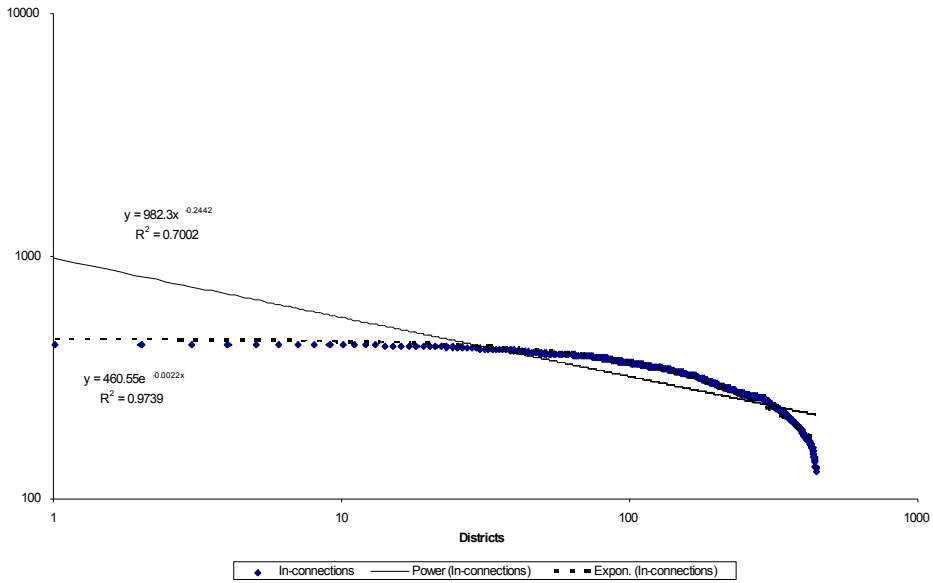
(b) 2005

Figure A-1: Log-log distributions of input degree, 1995 and 2005. Interpolating functions are power law (solid line) and exponential (broken line).
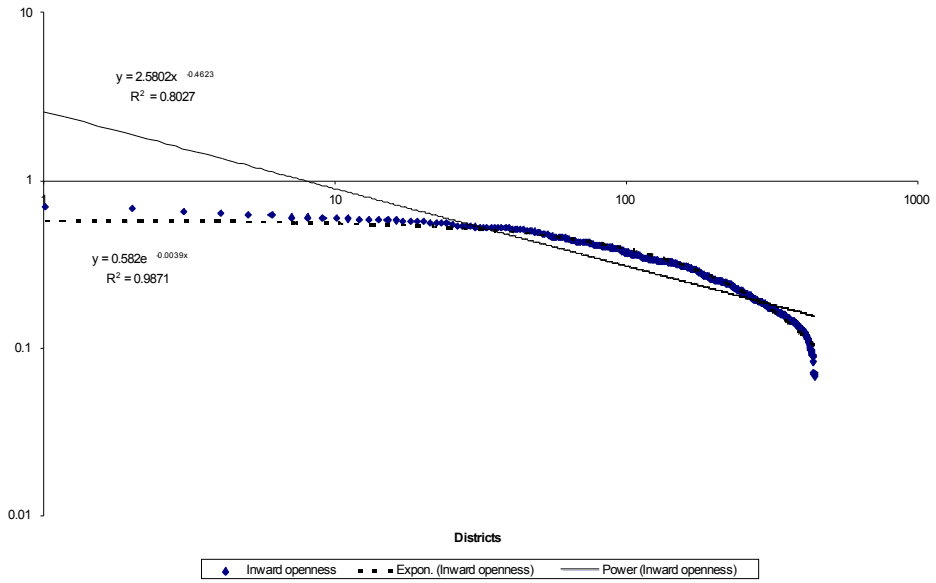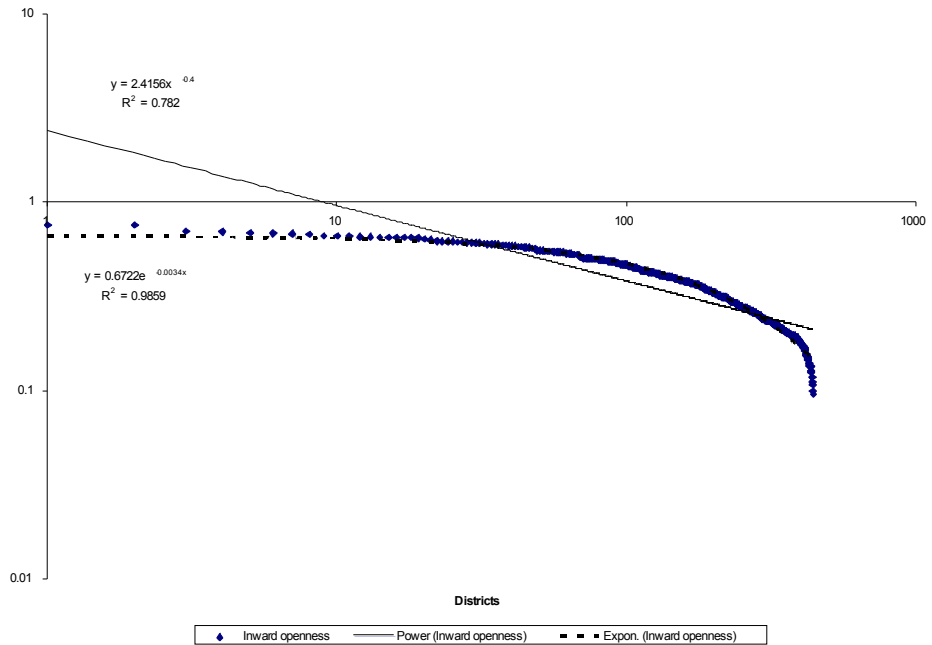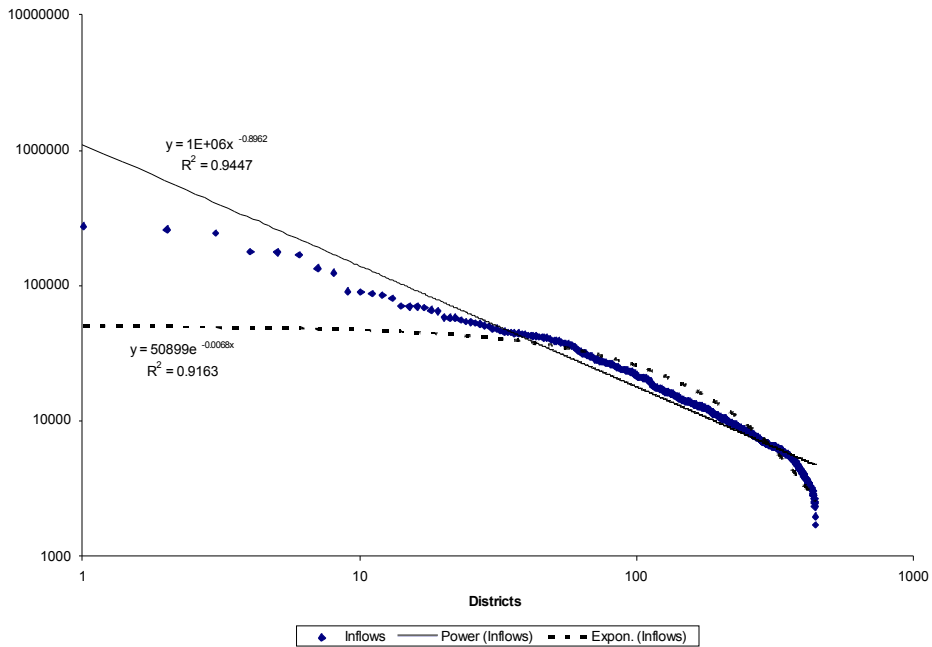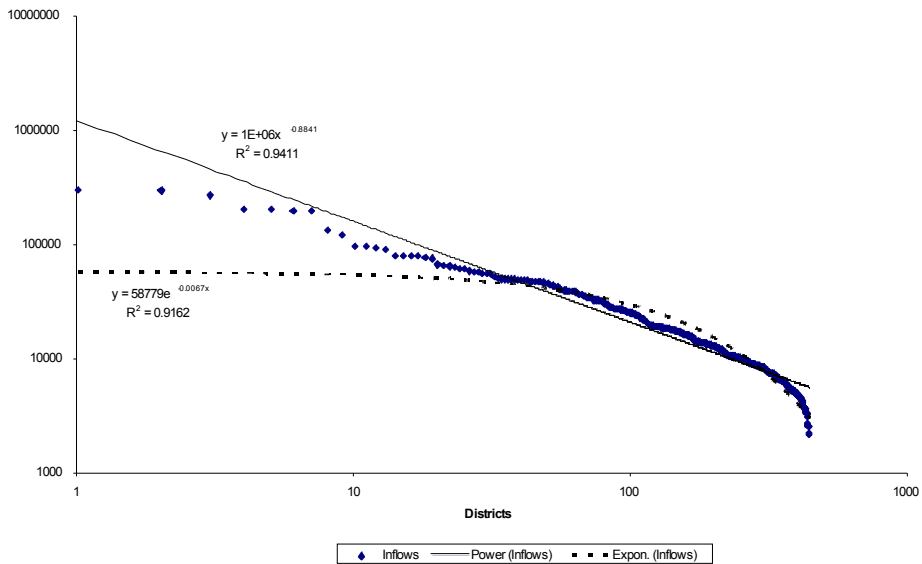
(a) 1995

(b) 2005

Figure A-2: Log-log distributions of inward openness, 1995 and 2005. Interpolating functions are power law (solid line) and exponential (broken line).

(a) 1995

(b) 2005

Figure A-3: Log-log distributions of inflows, 1995 and 2005. Interpolating functions are power law (solid line) and exponential (broken line).