

A Longitudinal Network Analysis of the German Knowledge Economy from 2009 to 2019: Spatio-Temporal Dynamics at the City–Firm Nexus

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Abstract

Multi-location knowledge-intensive firms span their value chains and thus their locations across space. Increased globalization alters the spatial configuration of such networks of knowledge creation. Longitudinal social network analysis allows detecting temporal changes in the arrangement of nodes and edges in the network and resulting changes in the overall structure. We use this approach to study for Germany the spatio-temporal dynamics of knowledge-intensive services firms – advanced producer services (APS) – in the years between 2009 and 2019. Multi-location APS firms are considered as vanguard of spatial structural change and thus lending to study their location choice behavior. A common approach is to analyze a one-mode intercity network where cities are the nodes. We take a different approach and include the firms’ perspectives. We work directly with the original data structure of a two-mode network including cities and firms as two node sets and we apply stochastic actor-oriented models for network dynamics. Results show that the spatio-temporal dynamics are characterized by both agglomeration and network economies. On a local scale, APS firms continue their location expansion over time and concentrate in agglomerations where many other APS firms and a greater availability of workforce are present. Simultaneously, they also choose new locations in agglomerations further apart from their present locations. On a supra-local scale, the network grows denser over time. Agglomerations that are attractive for APS firms in 2009 become even more attractive in 2019. Our analysis contributes to an understanding of how interactions amongst cities and firms on a local scale give rise to the empirically observed network patterns on a supra-local scale.

Keywords: Intra-firm networks, Spatio-temporal dynamics, Stochastic actor-oriented models, Two-mode networks, Germany, Advanced producer services

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Introduction

Background

The knowledge economy strongly affects spatial development in advanced economies. The knowledge economy is characterized by an accelerated pace of technological and scientific advancement, whereby the process of knowledge generation and dissemination and its spatial manifestation move more and more to center stage (van Tuijl and Carvalho 2014). Firms use highly specialized skills and knowledge from different parts of the value chain in order to sustain competitive advantage and create innovations (Lüthi, Thierstein, and Bentlage 2011; Faulconbridge, Hall, and Beaverstock 2008). Hereby, advanced producer services (APS) play an important role as they take over important intermediary functions for the rising global economic system (Lüthi et al. 2011). Saskia Sassen was the first to highlight the importance of APS for the understanding of contemporary cities in globalization and described them as spearheads of today's economy (Sassen 2001). They are defined as activities that “provide specialized services, embodying professional knowledge and processing specialized information to other service sectors” (Hall and Pain 2006:4). Examples for APS are the consulting firm McKinsey, the hard- and software developer Microsoft or the accounting firm Ernst & Young. APS increasingly locate in a selected number of cities hosting the management and servicing functions that produce the globalization of economic activities (Lüthi et al. 2011). New York, London, and Tokyo are examples of such “global cities” that serve as command and control centers of the global economy (Gottdiener and Budd 2005). Overall, knowledge-intensive firms develop their location network as part of their global business strategy. As they (re-)organize the geographies of their knowledge creation, we observe new forms of functional differentiation and new forms of hierarchical and network development between cities (Lüthi, Thierstein, and Bentlage 2010).

The relational perspective became evident since locations and firms co-evolve through networked interaction. This means that network and behavior are interdependent. Behavior can affect the network structure, e.g. when firms change their location network. In turn, the network structure can also affect behavior, e.g. when locations become more attractive for firms. The network approach and its corresponding tools of network analysis are becoming increasingly popular in urban research. Already more than 20 years ago, Manuel Castells observed that “the new economy is organized around global networks of capital, management, and information, whose access to technological know-how is at the roots of productivity and competitiveness” (Castells 1996:471). This resulted in the emergence of his “space of flows” concept that replaces eventually the “space of places” concept (Castells 1996). Whilst the “space of flows” does not indicate a particular methodological contribution, it is an important change in thinking by promoting a network logic instead of place-centricity (Anttiroiko 2015). The spatial implication of such a network logic is gaining in importance on the research agenda (Reades and Smith 2014; Zhang et al. 2018; Weber et al. 2020). A network consists of nodes that are connected through ties (Borgatti, Everett, and Johnson 2018). Generally, ties can be of different nature, e.g. cooperation, information flow, or monetary exchange. Hence, the focus is on relations between nodes. In order to apply the network perspective to urban research, a “nodalization” is necessary and common practice (Parr 2002; Lüthi et al. 2010). Hereby, researchers abstract locations into nodal regions (Costa Da Silva, Elhorst, and Silveira 2017). In the context of spatial network analysis, these nodes usually denote urban areas (Zhong et al.

2014). This spatial dimension is apparent in contemporary globalization in general (Therborn 2011) and in intercity networks in particular (Boix and Trullén 2007; Taylor et al. 2013). Overall, the concept of networks is deemed useful nowadays for making sense of cities and regions in an increasingly complex world (van Meeteren, Neal, and Derudder 2016).

In order to be innovative and sustain competitive advantage, firms combine highly specialized knowledge and skills from different parts of their value chains across the globe. When firms locate the individual elements of their value chains across multiple national and international locations, we can trace two main effects: agglomeration economies and network economies. Agglomeration economies describe a process of spatial concentration, where being geographically close to each other facilitates interactions between firms. This leads to benefits like information spillovers as well as sharing the labor market and infrastructure (Rosenthal and Strange 2003; Rozenblat 2010). As early as 1890, Alfred Marshall found that highly interconnected and co-located firms profit from trust, reduced transaction costs, growing productivity, and incremental innovations (Marshall 1890). Although Marshall used the term industrial districts, these mechanisms are not restricted to specific economic sectors (van Meeteren et al. 2016). On the other hand, network economies describe the opposite process of spatial spread, where firms profit from being integrated into a global network. By spreading their activities across space, they can source inputs all over the world, gain access to new markets and profit from international knowledge spillovers (Huggins and Thompson 2017). Information and communication technologies facilitate knowledge exchange across long distances (Bentlage 2014). Through network economies, innovations are possible in every place of the world. Seemingly oppositional, both effects – agglomeration economies and network economies – complement each other (Cabus and Vanhaverbeke 2006) and happen simultaneously (van Meeteren et al. 2016).

Frameworks for analyzing city-firm relations

The division of labor creates an intricate network of intra-firm and extra-firm activities, which form a firm's individual value chain. Knowledge-intensive firms organize their knowledge creation process through firm-internal business relations. These intra-firm networks are one important approach in studying economic globalization processes (Lüthi et al. 2010). Research on intra-firm networks studies phenomena within firms, e.g. the amount and relevance of information and knowledge transmitted through branch location networks of firms (e.g. Pred 1977; Rozenblat 2010; Taylor 2016). The Globalization and World Cities Study Group (GaWC) studies the formation of the world city network (Taylor 2016). The GaWC Study Group conceptualizes cities as being connected through flows of knowledge and information generated within a firm's location network and developed for analytical purposes the Interlocking Network Model (INM) (Taylor 2016). The INM is based on intra-firm location networks of APS firms. The model measures the connectivity between global cities based on multi-branch APS firms as they organize business activities across their offices worldwide (Pain and Hall 2008). The inter-city relations created by these firms are a proxy for estimating potential knowledge flows between cities. These flows are used to calculate a city's interlock connectivity, i.e. its integration into the world city network. For a city, being connected to other cities through such a network facilitates the globalization of economic processes. The most prominent result of the GaWC research is a ranking of global network connectivity for world cities. Such a ranking of leading cities is discussed on a global scale, for individual countries or industries.

The GaWC approach faces an extensive body of critique (e.g. Neal 2013; Burger, Meijers, and van Oort 2014; Liu et al. 2014). For our research, we see two important issues. First, the GaWC approach collects data about which firms are located in which cities in the form of a *city × firm* matrix. An interlocking network is described even as triple layered-network: “the net-level is the space of flows in the world economy, the nodal level is the cities, and the sub-nodal level is the advanced producer service firms” (Taylor, Pengfei, and Derudder 2011:4). However, in the INM itself, the data are projected into a *city × city* matrix and the analysis focuses only on connections between cities or intercity network structures. By doing so, the firm information is no longer available. In consequence, the city-firm nexus is lost. The city-firm nexus means understanding how firms behave and perform in certain territories (Hsu 2006). Second, the GaWC approach neglects the spatial dimension of the data. It treats cities as nodes; however, they no longer have a geographic dimension. Therefore, we cannot study how economic activities are linked to geographic locations. Hence, analyzing spatial processes of agglomeration and network economies is not possible. These two aspects are not necessarily shortcomings of the GaWC approach. Rather, we argue that they can be relevant and insightful complements, which we demonstrate in this paper.

Beyond the GaWC Study Group, there have been different approaches for analyzing city–firm relations in recent years. Garas, Rozenblat, and Schweitzer (2015) assess the performance of a city in the globalized economy. The authors use the original *city × firm* matrix to study how specialized or diversified each city is with respect to a global context. Another approach by Liu et al. (2013) further integrates a temporal dimension. The authors also use the original *city × firm* matrix and study how underlying processes of firm dynamics explain observed network changes globally. Despite focusing their research on cities, there is no focus on spatiality in the context of the knowledge creation process of firms.

Contextualizing city–firm relations

Germany is an interesting case for studying the functional and spatial dynamics of the knowledge economy since it is Europe’s biggest economy in global terms and it has a decentralized federal and urbanized structure. Whilst the populations of the largest cities like Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf are growing, small- and medium-sized cities lost inhabitants from 2005 to 2015 (BBSR 2017). A decreasing density in the use of demographic and economic assets can still be observed today in Eastern Germany (Lang 2012). These disparities play an important role regarding location decisions of firms (Lang 2012). Our current knowledge about the German knowledge economy space originates from either place-based or firm-based approaches.

Regarding place-based approaches, Wood (2006) finds that various urban centers have increased their specialist knowledge bases. The dynamics of knowledge exchange in APS firms have increased regional economic inequality in Germany (Wood 2006). Hoyler (2008) uses the INM to analyze Germany’s connectivity changes from 2000 to 2008 in relation to the global world city network of APS firms: German cities have experienced a connectivity decline and, hence, lower integration into the world city network. Three out of 10 global cities with the highest decrease in relative connectivity are in Germany: Cologne, Düsseldorf, and Frankfurt (Derudder, Hoyler, and Taylor 2008).

Firm-based approaches are mostly focused on measures on innovation and employment. Studying employment, Brinkley and Lee (2007) found that Germany had the most extreme increase in knowledge-based service employment in Europe. From 1995 to 2005, knowledge-based service employment increased by 26%, whilst less knowledge-intensive services increased by only 2 percent (Brinkley and Lee 2007). In line, Growe (2016) found a general increase of knowledge-intensive business services from 1997 to 2011 in Germany. The largest increases occurred in legal consultancy, advertising, and data management professions (Growe 2016).

Longitudinal studies of the German knowledge economy are nevertheless rare, due to the lack of panel data. The little that exists focuses either on firms or on cities. On the one hand, the nexus between firm networks and city networks has been missing so far. We lack insights into the dynamics at the firm level, which lead to the observed spatial patterns between cities on a macro scale. On the other hand, we see a need for more longitudinal research: A longitudinal approach can yield more insights since the dynamics of network evolution are of interest and generate the observed network patterns (Steglich and Knecht 2009).

In this study, we add to existing research about the German knowledge economy space in three ways. First, we add a temporal dimension and use a longitudinal approach. Second, we study the city–firm nexus, the link between the city and the firm dimension. Integrating both in our analysis increases complexity, but allows us to study how APS firms behave and perform in Germany. Third, we consider the spatial dimension of our data in order to study spatial processes in the city–firm network. Combining these three aspects, we analyze which spatio-temporal dynamics the German knowledge economy shows between 2009 and 2019.

The paper is structured as follows: the second section discusses our data and the methodology of data collection and analysis. The third section formulates our research question and hypotheses about the spatial development of the knowledge economy in Germany from 2009 to 2019. The fourth section presents our results, starting with a descriptive network analysis, followed by a modeling approach. The fifth section discusses and wraps up our findings and indicate possible streams of future research.

Data and methods

In operationalizing APS, we have followed a sector approach proposed by Legler and Frietsch (2006) and Gehrke, Frietsch, and Neuhäusler (2013). The authors have published a list of knowledge-intensive services based on the German classification of commercial sectors (WZ-2008). The relevant industries show a high share of participation in activities of knowledge generation and activities for strengthening the advancement of human capital (Gehrke et al. 2013). Our definition of APS includes the following sectors: accounting, advertising and media, banking and finance, insurance, law, management- and IT-consulting, information and communication services, 3rd and 4th party logistics, design, architecture, and engineering. This operationalization includes knowledge-intensive sectors that go beyond the GaWC approach. We have built the 2019 dataset by identifying the 30 largest firms in terms of employees for each APS sub-sector using the German Hoppenstedt database. Hoppenstedt is one of the largest business data providers in Germany and includes over 245,000 profiles of German companies, their sectors and the major industrial associations in Germany. We have a similarly constructed

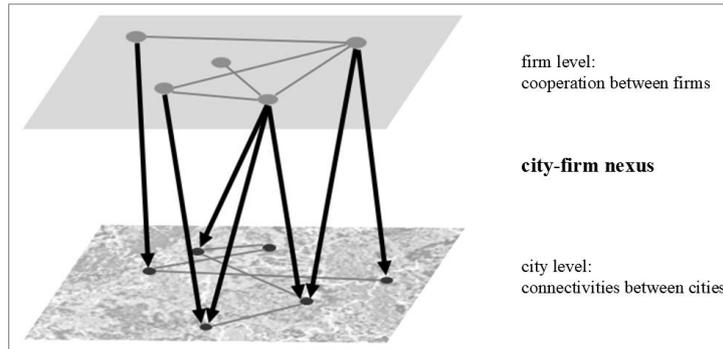


Figure 1. Schematic representation of our two-mode network.

dataset for 2009 from a previous project (Lüthi et al. 2011). In our panel, we examine companies that are among the top 30 largest firms in terms of employees in both 2009 and 2019. Previous studies also built the panel by identifying firms with the same name at both time points (Liu et al. 2013). Our rationale is that we are interested in the city–firm nexus. We intend to analyze the spatial behavior of these firms. We do not intend to study individual firms’ organizational structures like mergers and acquisitions. In the data collection, we gather information about the firms’ locations from their homepages. The locations are either documented as “1” (present) or “0” (no location). Our analytical spatial building blocks are 186 functional urban areas (FUAs) – or agglomerations – in Germany. The concept of FUAs was developed by the European Spatial Planning Organization Network (ESPON 2005). They are defined as having an urban core of at least 15,000 inhabitants and a total population of over 50,000. For each FUA, the potential area that can be reached within 45 minutes by car from the FUA center has been calculated. FUAs reflect the actual functional orientation of firms, communities, and people and, hence, allow a more realistic mapping of economic activity (Garas et al. 2015). Since labor market pooling was found to happen in FUAs based on commuting patterns (Larsson 2014), we regard it as the suitable spatial scale for our analysis. All in all, the final network panel consists of 139 firms and 186 FUAs in the form of a two-mode network.

In the two-mode network, the first node set are the firms and the second node set are the cities. The nodes are connected through ties only between the different node sets, not within them. The first node set holds agency, meaning the firms decide in which cities they want to locate. However, the cities – in our case the FUAs – can influence this decision through their characteristics. Figure 1 gives a schematic representation of our two-mode network. The top level represents the firm level. A network structure arises through collaboration between or within firms. This one-mode firm network is usually analyzed through methods of social network analysis. The bottom level represents the city level. A network structure arises through cities that are connected through firms operating in them. This one-mode city network is usually analyzed through the interlocking network model. Our focus is on the link between both levels: on the city–firm nexus. When a firm opens a new location, it establishes a new tie to a city. Since the firm holds agency, it sends a tie to a city. Therefore, the number of outbound ties from a firm to all cities it is located in is called the firm’s outdegree. Hence, the cities receive ties from firms. Therefore, the number of inbound ties from all firms to a city is called the city’s indegree.

We will first conduct a descriptive network analysis for the changes in the network from 2009 to 2019. We are interested in the change in overall network density. It is calculated separately for the two time points by dividing the number of existing links between firms and cities by the

number of theoretically possible links. In order to make sure that our data are suitable for stochastic actor-oriented models, we calculate a measurement of similarity between the successively observed networks. This measure is called the Jaccard index and is calculated as:

$$\frac{N_{11}}{N_{01} + N_{10} + N_{11}},$$

where N_{11} is the number of existing ties that remain unchanged from one point in time to the next. N_{01} is the number of newly established ties, and N_{10} is the number of deleted ties. As a rule of thumb, values below 0.2 indicate that the changes in the network might be too high to consider the data as an evolving network and use stochastic actor-oriented models (Ripley et al. 2019). Values of 0.3 and higher are suitable for this method (Ripley et al. 2019). Lastly, we are also interested in the change of indegree distribution of the FUAs. Indegrees simply count how many firm locations there are in each FUA for each point in time.

We then test the hypotheses statistically using a stochastic actor-oriented modeling approach. In our network data, the fundamental statistical principle of independence is not fulfilled. Hence, the standard methods of multivariate statistics cannot be applied. Therefore, we choose the stochastic actor-oriented modeling approach. The benefit of this approach is that we can apply statistical methods to our structurally dependent network data. The main idea of stochastic actor-oriented modeling is that the evolution of a network is both a result of its members' characteristics and its structural features (Maggioni and Uberti 2011). We work directly with the two-mode network. Continuous time Markov chains for modeling longitudinal networks were already introduced in 1977 and have been significantly improved upon (McCulloh and Carley 2011). However, in particular models for two-mode data are very recent and still under development; Koskinen and Edling first proposed them in 2012 (Koskinen and Edling 2012). In our model, firms as the first node set hold agency, meaning they decide whether and in which places they install or remove office locations. We have taken the network observed in 2009 as a starting point. We then simulated the evolution to 2019. If the obtained network is – within certain boundaries – similar to our observed 2019 network, we assume that the processes are a good approximation of the actual network dynamics. The simulation of the evolution assumes that “the network changes continuously as the result of choices made by the individual actors, while the present network structure represents the social context that influences the actors' choices, and changes as a result of them” (Maggioni and Uberti 2011:1043). The simulation divides our two time points of discrete time into continuous time: the two time periods of 2009 and 2019 are split into smaller and smaller time periods, which in effect is then continuous. We call each of these very small time periods a micro-step. In each micro-step, one firm is drawn to make a move. A move means to establish a new location, to remove a location, or to do nothing. For a detailed introduction into stochastic actor-oriented models for network dynamics, see Snijders, van de Bunt, and Steglich (2010). We work with the R package RSiena, short for Simulation Investigation for Empirical Network Analysis (Ripley et al. 2019).

In the next section, we will present the research question and hypotheses.

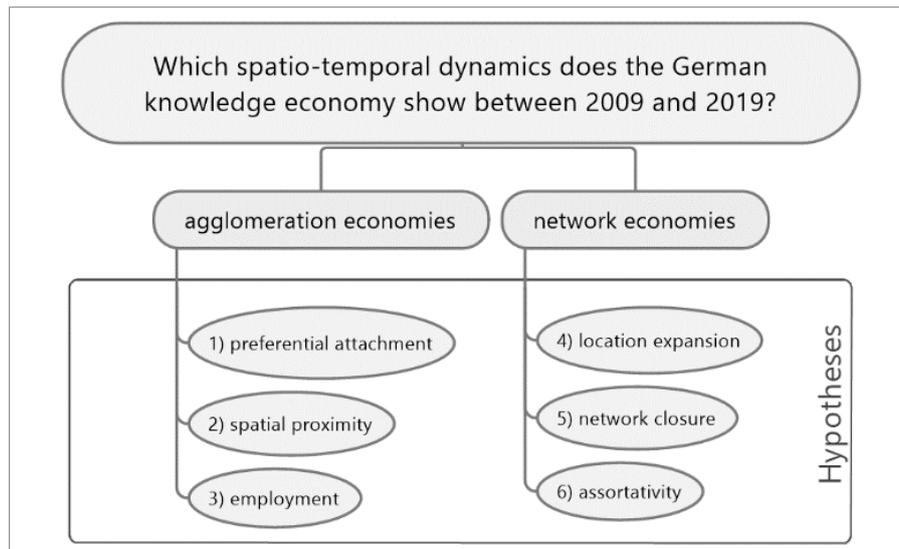


Figure 2. Overview of hypotheses

Research question and hypotheses

In order to study the city–firm nexus and to incorporate a temporal dimension, we have formulated the following research question: Which spatio-temporal dynamics does the German knowledge economy show between 2009 and 2019? Our research focuses on six hypotheses (Figure 2). The first three hypotheses reflect processes of agglomeration economies, where we expect to find tendencies of spatial concentration. We label them “preferential attachment”, “spatial proximity”, and “employment”. The other three hypotheses reflect processes of network economies, where we expect to find tendencies of spatial spreading. We label them “location expansion”, “network closure”, and “assortativity”. We now explain our hypotheses in detail. The implementation in RSiena and the formulas for the effects are displayed in Appendix A.

H1: The functional urban areas (FUAs) that hosted many firms in 2009 tend to host more firms in 2019. The preferential attachment process is significant and positive.

Preferential attachment is an indegree-related popularity effect (Ripley et al. 2019). It is a structural effect that depends on the network only. It tests whether nodes with higher indegrees tend to increase their indegrees even further. In our context, we test whether over time, nodes from the first node set (firms) primarily connect to already large nodes from the second node set (FUAs) (Ducruet and Beauguitte 2014). We use the square root version of this effect. It usually performs better empirically in the computation (Snijders et al. 2010). Further, we want to express a diminishing return of high degrees as suggested by Derudder et al. (2010). It means that whether a German FUA hosts 2 or 10 firm locations makes a rather big difference. But whether it hosts 100 or 108 locations is no longer as important. In the view of agglomeration economies, we argue that firms tend to concentrate in the same location in order to profit from knowledge spillovers and shared labor market and infrastructure. Hence, German FUAs that host many firms are more attractive for new firms to locate in.

H2: Firms tend to open up new locations in spatial proximity to FUAs where they are already present.

Spatial proximity is a dyadic covariate effect that tests the closure of a covariate (Ripley et al. 2019). In our context, we implement it through a distance matrix of the German FUAs. The distance is measured in Euclidean distance in meters. In our model, the distance matrix is a covariate on the FUA node set. A significant negative parameter indicates that firms tend to locate closer together; a significant positive parameter indicates the contrary. Even though the digital transformation is changing our current economy, physical proximity is still important and cannot be replaced by virtual services (Lyons, Mokhtarian, and Dijst 2018). When firms open a new location, we expect that they tend to choose FUAs that are in spatial proximity to their present location. For example, a firm headquartered in Munich might open up a new local branch in Augsburg being about 45 minutes travel time away. By doing so, the firm can obtain greater market coverage and, at the same time, easily keep face-to-face contacts within its location network in a familiar economic environment.

H3: Firms tend to open up new locations in FUAs that have a higher level of employment.

Employment is an actor-dependent covariate (Ripley et al. 2019). We want to find out whether firms, overall, prefer FUAs that have a higher level of employment in APS. Here, we took the number of persons employed in APS that are subject to social security contributions in Germany in 2009. We treated this information as a covariate on the FUA node set. This is a purely monodyadic covariate effect. We used the data from 2009 since this is our starting point from which we modeled the location decisions. In the view of agglomeration economies, we expect firms to locate preferably in FUAs that have a higher amount of available workforce. Our assumption is based on the research about human capital externalities in cities (Liu 2014; Peters 2020).

H4: Firms that already had many locations in Germany in 2009 continue their location expansion and have established even more locations in 2019.

Location expansion is a structural effect (Ripley et al. 2019) that has no spatial dimension. It tests whether over time, nodes from the first node set (firms) establish more connections to nodes from the second node set (FUAs), regardless of the FUAs attributes. In network terms, we tested whether nodes with higher outdegrees tend to increase their outdegrees even further. We also used the square root version of this effect. In the view of network economies, we expect firms that already have many locations to continue their spatial expansion in order to locate in even more German FUAs. By doing so, firms intend to expand their customer base and increase their market coverage.

H5: Firms co-located in one FUA in 2009 tend to co-locate in more FUAs in 2019; hence, there is a tendency for network closure.

Network closure is a structural effect (Ripley et al. 2019) that indicates whether firms who have one location in common also tend to make other location choices in common. Companies often move to places where other local companies also have moved (Liu et al. 2013). In the view of network economies, we thus expect that German FUAs become more connected through firm locations since firms are more and more co-located in the same FUAs.

Table 1. Changes in network 2009–2019.

	2009	2019		Change
Network density	0.086	0.099		□
Number of ties	2227	2559	640 new ties 308 deleted ties 1919 maintained ties	□
Jaccard index				0.669

H6: Firms with many locations are more likely to locate in FUAs that host few firms; hence, there is a tendency for assortativity.

Assortativity is also a structural effect that depends on the network only (Ripley et al. 2019). It tests whether actors with high outdegrees tend to tie themselves to actors with high indegrees (Ripley et al. 2019). In our context, we test whether firms that already have many locations tend to open new locations in FUAs that already have many firm locations. This is the connection between hypotheses four and one. In H4, we test whether large firms expand even more, regardless of the FUAs characteristic. In H1, we test whether popular FUAs become more popular, regardless of the firms characteristics that move there. A positive assortativity effect indicates that firms with many locations select popular FUAs. Conversely, negative assortativity indicates that firms with many locations select less popular FUAs. We expect that firms with many locations move to smaller cities as they are already present in major centers.

In the next section, we present the analyses of our network panel and the results.

Results

We start with the descriptive results of our network analysis (Table 1). The density tells us that the network per se is quite sparse, but it has become denser over time. Overall, firms have established around twice as many new locations as they have closed down. The Jaccard index is 0.669, which means that our network panel is relatively stable over time and well suited for stochastic actor-oriented modeling.

We display the change in indegree distribution for the German FUAs in Figure 3. Here, we plot the overall changes in the amount of firm locations from 2009 to 2019. It could be possible that some firms closed down locations whilst others opened up locations, so that overall there are no changes in the amount of locations. We see a scattered geographical pattern in Figure 3. The vast majority of FUAs have gained firm locations. The 121 FUAs that are colored in light green have gained up to 10 firm locations. Three FUAs colored in dark green have gained more than 10 firm locations: Hamburg and Leipzig (+14 firm locations each) and Duesseldorf (+12 firm locations). In total, 37 FUAs show no difference in the amount of firm locations – colored in grey. The 25 FUAs colored in red have lost locations; the maximum decrease in firm locations is in the FUA of Minden; it lost four firm locations.

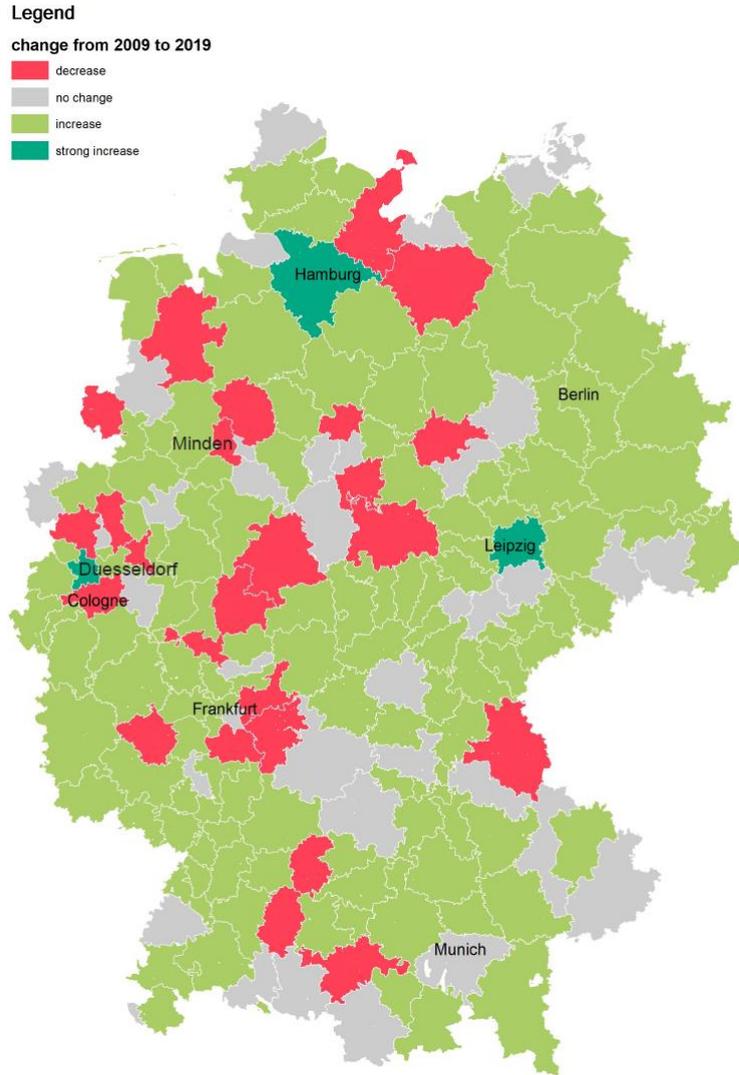


Figure 3. Change in indegree distribution for the German FUAs.

Whilst the descriptive analysis and visualization is an important first step, we cannot gain much information about possible spatio-temporal dynamics. Therefore, we now move on to the modeling results. We have employed a forward model selection strategy (Conaldi, Lomi, and Tonellato 2012). We have started with a null model, in which the objective function only accounts for the overall density effect, and then gradually included our six effects. The intermediate models are shown in Appendix B. We now discuss our full model in Table 2.

In our full model, the significant negative effect for out-degree density is included in the model by default and is comparable to the intercept in a regression model. A negative density effect means that firms are overall not likely to establish new locations. This makes sense intuitively since it is very costly, and firms do so only for a specific strategic purpose. We now continue to have a closer look at each effect that we have tested.

For Hypothesis 1, we find that the preferential attachment effect is positive and significant: The FUAs that hosted many firms in 2009 tended to host more firms in 2019. Examples are the FUA

Table 1. Modeling results.

	Null model			Full model		
	Estimate	Standard error	Convergence <i>t</i> -ratio	Estimate	Standard error	Convergence <i>t</i> -ratio
Density	-1.0048	(0.0398)	0.0435	-3.6868	(0.2869)	0.0304
Preferential attachment				0.4078	(0.0560)	0.0209
Spatial proximity				0.0070	(0.0021)	0.0162
Employment				0.8598	(0.1261)	0.0154
Location expansion				1.0295	(0.1279)	0.0286
Network closure				0.0132	(0.0013)	0.0354
Assortativity				-0.3041	(0.0391)	0.0450
Overall max. convergence ratio			0.0435			0.2342

Estimates in bold are significant at $p < 0.001$; estimates for all effects have reached convergence.

of Hamburg, which increased from 91 to 105 locations and Düsseldorf, which increased from 70 to 82 locations. We observe a concentration of our firms in these major FUAs in the sense of agglomeration economies. Firms showed a tendency to choose larger FUAs where a critical mass of other firms is present. This setting is attractive for firms since there is a shared labor market and infrastructure and the possibility to profit from knowledge spillovers.

For Hypothesis 2, the spatial proximity effect is included in the model as a distance matrix. The effect is positive and significant. This means that – contrary to our expectations – firms tended to open up new locations further apart from FUAs where they were already present. An example is the media company DuMont. Amongst others, it had locations in the FUAs of Frankfurt am Main, Halle and Cologne in 2009. Today, DuMont also has locations in the FUAs of Berlin and Hamburg. The firm did not choose to locate in adjacent FUAs, but in FUAs further away from their existing locations. This result shows that besides a concentration, also an opposite spatial behavior is observable. Firms showed a tendency to spread their locations across greater distances.

For Hypothesis 3, we find that the employment effect is positive and significant: when choosing a new location, firms tend to decide on FUAs with a higher level of employment in APS. For example, Munich with around 225,000 people employed in APS, Hamburg with around 212,000, Frankfurt am Main with around 161,000 and Berlin with around 156,000. A larger pool of employees in APS is an attractive location factor for firms. This finding fits well to the result from Hypothesis 1. FUAs with a higher amount of firm locations and a larger available workforce are more attractive for firms than FUAs with a lower amount of firm locations and a smaller available workforce. In turn, this leads to a spatial concentration in the sense of agglomeration economies.

For Hypothesis 4, we find that the location expansion effect is positive and significant: firms that already had several locations in Germany in 2009 tended to establish even more locations in 2019. This holds true for most firms with a high amount of locations. An example is Deutsche Bank, which increased their locations from 166 in 2009 up to 177 in 2019. This effect does not reveal any spatial dimension of the firms' expansion. However, we observed a spread of firm locations in Germany in the sense of network economies.

For Hypothesis 5, we find that the network closure effect is positive and significant: Firms co-located in one city in 2009 tended to co-locate in more FUAs in 2019. For example, the two management and IT-consulting firms Deloitte and Cancom were both – amongst others – located in Düsseldorf in 2009. Deloitte was also located in Dresden in 2009. In 2019, Cancom also opened a location in Dresden, and both are now present in this FUA. We observed that firms tend to make more location choices in common. This in turn leads to FUAs being more connected in the sense of network economies.

For Hypothesis 6, the assortativity effect is the only effect that is negative and significant in our model. We have found that firms with many locations tended to choose FUAs that host few firms. Examples are Commerzbank (185 locations) and Deutsche Postbank (186 locations). These two banks are the only firms in our sample who have a location in the FUA of Nordhorn. No other firm in our sample is present in this FUA. We find that large firms expand into FUAs that are not popular amongst the other firms so far. In Hypothesis 4, we see that large firms expand even more, but we do not know where to. In Hypothesis 1, we find that popular FUAs became even more popular, but we do not know for which firms. Now we can understand the connection: larger firms tend to locate in smaller FUAs. These firms are already present in all major FUAs and move to smaller FUAs in order to benefit from network economies. In contrast, smaller firms tend to locate in larger FUAs in order to benefit from agglomeration economies.

Our assumption is that APS is not a homogenous set of firms, and we expect different sub-sectors to exhibit different spatial behavior over time. Therefore, we calculate the Jaccard indices for each sub-sector individually. We have found that advertising and media as well as design, architecture and engineering are the most dynamic sectors, where the most location changes took place from 2009 to 2019. In contrast, law, baking, and finance as well as accounting are the most stable sectors with the fewest location changes in our period of analysis. These single sub-sectors in our panel are quite small, ranging from 10 to 25 firms. For this reason, it is not feasible to run a stochastic actor-oriented model on them individually (Annenberg School of Communication 2012). Therefore, we have tried to re-aggregate the individual sectors into groups.

A first group consists of banking and finance as well as insurance. We suggest grouping them as “financial sectors”, based on Pratt (2008). A second group consists of accounting, law, management, and IT-consulting. We suggest grouping them as “services sectors”, based on the GaWC research group (Taylor 2016). A third group consists of advertising and media, design architecture and engineering, as well as information and communication services. We suggest grouping them as “creative sectors”, based on Pratt (2008). The high-end logistics sector is not considered here, we do not see how logistics would fit in any of the groups. The Jaccard indices for the three groups are as follows: 0.750 for financial sectors, 0.723 for service sectors, and 0.518 for creative sectors (Table 3). In other words, the financial and service sectors are quite

Table 2. Descriptive and modeling results for the three sectors.

	Financial sectors	Service sectors	Creative sectors
Sub-sectors	Banking and finance, insurance	Law, accounting, management/IT consulting	Information and communication services, Design, architecture and engineering, advertising and media
Σ	35 firms	56 firms	36 firms
Jaccard index	0.750	0.723	0.518
Preferential attachment	-0.01	0.06	0.01
FUA employment	0.22	0.60	0.88
Location expansion	-	0.04	0.04
Assortativity	-	-0.03	-

Estimates in bold are significant at $p < 0.001$ (for financial sectors: $p < 0.1$); estimations for all effects have reached convergence. A dash means that this effect has not been tested.

similar and show a high similarity between the two time points. The creative sectors have a lower similarity; there occurred more changes in the configuration of locations.

We will now run a stochastic actor-oriented model on the three sectors. It is important to mention that we cannot test all hypotheses for the financial and creative sectors. Since these networks only contain a smaller number of firms, we calculate models with fewer effects in order to obtain converged models. We show the most important modeling results in the lower half of Table 3.

All knowledge-intensive firms – regardless of their specific economic activity – consider a higher level of employment in APS as an important location factor. However, we also find differences between the three sectors.

A main explanation for the spatio-temporal dynamics of the financial sectors is the specific spatial logic of the German banks. The banking system in Germany is decentralized as a consequence of the specific regional structure of the Federal Republic (Klagge, Martin, and Sunley 2017; Gärtner and Fernandez 2018). In spatial terms, this means that head offices as well as decision-makers are in close proximity to their clients (Gärtner and Fernandez 2018). In 2009, there already was a dense network of branch banks, and the banks were present in all the major locations where they have clients. The authors found that there was a strong increase in the market share of decentralized banks in Germany (Gärtner and Fernandez 2018). For this reason, we do not find tendencies for agglomeration economies in our data. There are even tendencies to choose less popular FUAs, although the estimate is not significant. Research also shows that German banks are much more regionally embedded and linked more closely to clients and regions than in more centralized European countries like Spain (Gärtner and Fernandez 2018).

In the services sector, we have the “big four” consultancies of EY, KPMG, PWC, and Deloitte in our sample. These and other large global transnational firms mainly grow internationally (Morgan and Quack 2005). Hence, law firms need to be able to negotiate deals through multiple national jurisdictions. They do so through either forming partnerships or by setting up own international offices through transferring partners overseas and hiring local lawyers (Morgan and Quack 2005). In contrast, we also have smaller national firms in our sample like Falk. These firms predominantly operate on a national scale. These national firms tend to maintain strong connections to the local labor market and its knowledge base (Morgan 2006). Combining both mechanisms, we observed agglomeration economies in the German services sector as firms choose to locate in popular German FUAs. We also observed network economies as larger firms expand their location network. Interestingly, these larger firms do not tend to locate in popular FUAs.

In the creative sectors, Karlsson and Picard described a strong concentration in a few large cities due to benefits of co-location (Karlsson and Picard 2011). The authors use the term “large media centers” to describe cities in which global media firms prefer to locate in order to gain access to new markets and increase their turnover (Karlsson and Picard 2011). We consider Berlin, Hamburg, Cologne, Munich, and Stuttgart as the major media cities in Germany. However, all these FUAs lost firms in the period of our analysis. A possible explanation is the increasing speed of technological change in recent years (Kamp and Parry 2017). It makes products and services transportable electronically and without cost through space (Quah 1999). This can explain why we did not find tendencies towards agglomeration economies in the creative sectors in our sample. In contrast, we found tendencies towards network economies. Larger creative firms tend to expand their location network and establish locations in FUAs where fewer firms are located. Despite the technological changes, creative firms seem to value proximity to their customers, suppliers and cooperation partners (Helbrecht 2005; Zhao, Bentlage, and Thierstein 2017) and presumably move to where these are located.

In the next section, we will discuss our results, put them in a broader context and show possible ways for future research.

Discussion and conclusion

This research used a two-mode network structure to analyze the city–firm nexus in the German knowledge economy from 2009 to 2019. Our analysis shows two main insights. First, spatio-temporal dynamics are characterized by both agglomeration economies and network economies. Second, a differentiation between spatial scales shows how interactions among FUAs and firms on a local scale can explain the empirically observed network pattern on a supra-local scale. We will now discuss these findings.

Let us have a closer look at the first result. In terms of agglomeration economies, we find that FUAs that hosted many firms in 2009 have attracted more firm locations and host even more firms today. Firms concentrate in FUAs where many other firms are present. This holds true especially for the services sectors. Our findings confirm aspects of agglomeration economies in literature (e.g. Brown and Rigby 2013; Neal 2016). The authors describe that firm-external expansion determinants concern the characteristics of the location, which attract firms to a destination. These factors are – amongst others – an adequate market, infrastructure, and labor

pool, as well as the presence of similar firms (Brown and Rigby 2013; Neal 2016). Agglomeration economies yield exactly these benefits. We can confirm the dynamics of agglomeration economies through the factors of labor pool and presence of similar firms for the German knowledge economy.

In line with the benefits of agglomeration economies, we expected to find that firms tend to cluster spatially. In contrast, we find that firms have a tendency to open up new locations further apart from FUAs where they are already present. We argue that they do so in order to profit additionally from network economies. In terms of network economies, we find that knowledge-intensive firms continue their location expansion in Germany. This holds true especially for the services sectors and creative sectors. Although the digital transformation continuously changes the knowledge economy as more services are provided online and on demand and the number of physical locations reduces, we do not observe any cutback in firm locations so far. Firms still seem to prioritize being close to their customers for providing advanced producer services because they can expand their market presence and spread their intra-firm networks. Firms with a large number of locations especially continue their nationwide expansion and establish even more locations. These firms can source inputs and gain market access across the country by spreading their activities across Germany and by increasing their presence overall. In addition, we can also specify where these large firms tend to locate. Their service network already covers almost the entire country, and being close to customers is important. Therefore, firms with many locations tend to choose FUAs that host few firms. We argue that these firms do not specifically choose between locating in FUAs with fewer firms over FUAs with more firms. Instead, we interpret this effect as firms, which have many offices are already present in major FUAs. When expanding their intra-firm network they move into FUAs with fewer firms for two reasons. First, because they are not yet present there and second, because they want to provide face-to-face services – like after-sales training – for their customers nationwide.

We observe that firms, which have one location in common also tend to make other location choices in common. Liu et al. (2013) found the same result: the authors studied the largest global APS firms in terms of employees. The authors interpreted this finding as firms copying or following each other's location strategies. Instead, we would argue that FUAs become more and more similar in terms of the firms they host. Major banks or law offices are present in all major cities (Hoyler 2011) and the firm mix has assimilated more and more between FUAs. Overall, we find that the amount of firm locations has increased and the city–firm nexus has become stronger. Nevertheless, literature is ambiguous about that finding. Whilst some report an increasing closure of locations in Germany among, e.g. banks (Schwartz, Dapp, and Beck 2017), others report increasing investments in these locations based on clients' demand for on-site advisory services (Rensch 2015).

Let us have a closer look at the second result. We will now differentiate our empirical results between a local and a supra-local scale. The local scale can be understood as the firm logic, where interactions between FUAs and firms happen. On the local scale, firms decide to locate in specific places. Here, we find certain tendencies when firms open up new locations. We formulate these tendencies as a firm's theoretical location decision between two locations under the *ceteris paribus* condition. In terms of agglomeration economies, a firm would tend to choose the FUA where more firms are present. It would also choose the FUA with a higher level of APS employment. Further, the firm would be more likely to locate in the FUA that hosts a firm with which it currently already shares a location. In terms of network economies, a firm would

choose the FUA further apart from its present location. When we zoom out to the supra-local scale, we find how these interactions on the local scale are reflected in network patterns among FUAs. Here, we find tendencies for certain spatial dynamics: in terms of agglomeration economies, FUAs that are attractive for APS firms are becoming even more attractive. Lüthi et al. (2011) showed that the functional urban hierarchy of German FUAs was steep in 2009. A steep functional urban hierarchy means that the distribution of firm locations is rather uneven in Germany: whilst only a few FUAs host a large number of firms, many FUAs host smaller numbers of firms. Based on our result, we can add here that this hierarchy became even steeper from 2009 to 2019. In terms of network economies, APS firms are generally expanding their location networks in Germany, which leads to the network growing denser.

Overall, this research is one possible approach to tackling the challenge of analyzing and operationalizing the firm-location dynamics of knowledge-intensive firms. We chose to work directly with the original data structure in order to retain the firm information that is crucial for studying the city–firm nexus. We discovered that the spatio-temporal dynamics of knowledge-intensive firms are a complex interplay of agglomeration economies and network economies where no clear-cut distinction between the degree of the interplay of both mechanisms is possible. We argue that our study can add new insights into spatio-temporal network dynamics in two-mode networks in urban research and encourage researchers as well as federal agencies to increase their efforts in panel data collection. In a broader context, the stochastic actor-oriented modeling framework is a more useful approach for analyzing underlying network effects than a descriptive analysis of observed changes in network patterns. Especially working with the original structure of a two-mode network allows a more nuanced analysis of change by testing hypothesized effects in both node sets.

We have to keep three limitations in mind when interpreting our findings. First, we studied the largest APS firms, ranging from 281,000 employees in advertising and media up to 957,000 employees in logistics. This implies that we cannot make statements about the knowledge economy in Germany as a whole. Studies identified smaller firms as relevant parts of value chains as they often fulfill important supplier functions (Thierstein, Bentlage, and Pechlaner 2011). We tried further distinguishing our sample into financial, services, and creative sectors, which yielded more insights. Still, we suggest being careful with interpreting results from these sub-networks due to the somewhat arbitrary division and small sample size. Second, research is still uninformed about the causal direction and temporal development between agglomeration economies and network economies (Neal 2011). We provided evidence that both effects are at work at the same time in our study, but we cannot determine a causality here. Hand in hand, a last limitation in terms of methodology is the fact that the role, which causality can play in social network analysis is not yet fully understood (Doreian 2001).

When studying the city–firm nexus in any geographical context, it is important to incorporate both agglomeration economies and network economies in the longitudinal analysis. For future research, we suggest conducting a global-scale analysis: including also the global locations of these firms might be an even more suitable approach to analyzing network economies. A last comment for future research concerns a methodological issue. The assumption that the size of the effect relates to its relative importance in the network evolution holds only true when the effects are standardized. Currently, this is only possible for one-mode networks (Snijders 2020). Once solved methodologically, this will be a valuable extension for future research, allowing a

comparison of the relative strength of agglomeration economies and network economies effects and their interplay over time and spatial scales.

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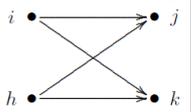
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Appendix A – Implementation in RSiena

Table 4 shows how we translate our hypotheses into effects implemented in the RSiena package version 1.2.14 (Ripley et al. 2018). The information is taken from the RSiena manual (Ripley et al. 2019).

Table 4. Translation of effects to be tested into RSiena.

Hypothesis	Effect	RSiena name	rFormula
		Density effect	$s_i(x) = x_{i+} = x_i + \sum_j x_{ij}$ <p><i>s</i>: effect; <i>i</i>: focal actor <i>x_{i+}</i>: outgoing tie from <i>i</i> <i>x_{ij}</i>=1 indicates presence of a tie from <i>i</i> to <i>j</i> <i>x_{ij}</i>=0 indicates absence of a tie from <i>i</i> to <i>j</i></p>
1	Firm activity	Outdegree-related activity (sqrt) effect	$s_i(x) = x_{i+}^{1.5} = x_{i+} \sqrt{x_{i+}}$
2	Preferential attachment	Indegree-related popularity (sqrt) effect	$s_i(x) = \sum_j x_{ij} \sqrt{x_{+j}}$ $= \sum_j x_{ij} \sqrt{\sum_h x_{hj}}$ <p>Sum of the square roots of the indegrees of the others to whom <i>i</i> is tied</p>
3	Firm-FUA assortativity	Out/in degree ^(1/2) assortativity	$s_i(x) = \sum_j x_{ij} x_{i+}^{1/2} x_{+j}^{1/2}$ <p>Differential tendency for actors with high outdegrees to be tied to actors with high indegrees</p>
4	Network closure	Number of four-cycles	 $s_i(x) = \frac{1}{4} \sum_{j,k,h \text{ all different}} x_{ij} x_{ik} x_{hj} x_{hk}$
5	Spatial spread	XW→X closure of covariate	<p>X: network in the role of the dependent variable W: effects that determine the dynamics of network X (here: geographic distance)</p> $s_i(x) = \sum_{j \neq h} x_{ij} x_{ih} w_{hj}$

6	(FUA employment)	Covariate-related popularity	$s_i(x) = \sum_j x_{ij} v_j$ <p>Sum of the covariate over all actors to whom i has a tie</p>

Appendix B – Detailed modeling results

	Null model			Model 1			Model 2			Full model		
	Estimate	Standard error	Convergence <i>t</i> -ratio	Estimate	Standard error	Convergence <i>t</i> -ratio	Estimate	Standard error	Convergence <i>t</i> -ratio	Estimate	Standard error	Convergence <i>t</i> -ratio
Density	-1.0048	(0.0398)	0.0435	-4.4373	(0.1566)	-0.0639	-5.4984	(0.3784)	-0.0069	-3.6868	(0.2869)	0.0304
Preferential attachment				0.4466	(0.0155)	-0.0730	0.4583	(0.0377)	0.0122	0.4078	(0.0560)	0.0209
Spatial proximity				0.0151	(0.0016)	-0.0308	0.0076	(0.0019)	-0.0746	0.0070	(0.0021)	0.0162
Location expansion							0.2874	(0.0504)	-0.0303	1.0295	(0.1279)	0.0286
Network closure							0.0007	(0.0006)	-0.0152	0.0132	(0.0013)	0.0354
FUA employment										0.8598	(0.1261)	0.0154
Assortativity										-0.3041	(0.0391)	0.0450
Overall max. convergence ratio	0.0435			0.0754			0.1570			0.2342		

Estimates in bold are significant at $p < 0.001$; estimates for all effects have reached convergence.

Appendix C – List of firms in the network panel (2019)

Banking and finance	
Deutsche Bank Commerzbank AG DZ Bank AG Landesbank Baden-Württemberg BayernLB Hamburger Sparkasse AG Landesbank Hessen-Thüringen Sparkasse Köln Bonn NordLB	HSH Nordbank AG Kreissparkasse Köln Deutsche Postbank AG DekaBank Deutsche Girozentrale Berliner Volksbank Gruppe Deutsche Börse ING-DiBa AG Aareal Bank AG
Logistics (3p and 4p)	
Deutsche Post AG Schenker AG DACHSER Group SE & Co. KG General Logistics Systems Germany GmbH & Co. KG Fiege Logistik Rhenus SE & Co. KG Kühne & Nagel (AG & Co.) KG	Hellmann Worldwide Logistics GmbH & Co. KG Hermes Germany GmbH TNT Express GmbH Rudolph Logistik Gruppe GmbH & Co. KG Oldendorff GmbH & Co. KG Hapag-Lloyd AG
Design, architecture and engineering	
Bilfinger SE HOCHTIEF Solutions AG EDAG Engineering GmbH Bertrandt AG FERCHAU Engineering GmbH	Brunel GmbH Altran Group Formel D GmbH Fichtner GmbH & Co. KG Drees & Sommer SE
Advertising and media	
Verlagsgruppe Georg von Holtzbrinck GmbH Axel Springer SE Hubert Burda Media Kommanditgesellschaft Heinrich Bauer Verlag KG Verlagsgruppe Passau GmbH ProSiebenSat.1 Media SE	BBDO Group Germany GmbH DuMont Mediengruppe GmbH & Co. KG Verlagsgesellschaft Madsack GmbH & Co. KG Ernst Klett Aktiengesellschaft Rheinisch-Bergische Verlagsgesellschaft mbH Süddeutscher Verlag GmbH
Law	
Freshfields Bruckhaus Deringer CMS Hasche Sigle Clifford Chance Linklaters Hengeler Mueller Taylor Wessing White & Case Luther	Beiten Burkhardt Gleiss Lutz Rödl & Partner Heuking Kühn Lüer Wojtek Baker & McKenzie Allen & Overy Latham & Watkins
Accounting	
PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft Ernst & Young GmbH Wirtschaftsprüfungsgesellschaft KPMG AG Wirtschaftsprüfungsgesellschaft BDO AG Wirtschaftsprüfungsgesellschaft Treuhand Hannover GmbH ADS Allgemeine Deutsche Steuerberatungsgesellschaft mbH BSB-GmbH Ebner Stolz Warth & Klein Grant Thornton AG Wirtschaftsprüfungsgesellschaft PKF Fasselt Schlage Partnerschaft mbB Wirtschaftsprüfungsgesellschaft Rechtsanwälte MUNKERT · KUGLER + PARTNER Mazars GmbH & Co. KG Wirtschaftsprüfungsgesellschaft	LBH-Steuerberatungsgesellschaft mbH DHPG BUST FIDES Revision KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft Buchstelle Landesbauernverband Solidaris Revisions-GmbH Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft Dornbach FALK GmbH & Co KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft ALPHA Steuerberatungsgesellschaft WIKOM AG BANSBACH GMBH Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft CURACON GmbH Wirtschaftsprüfungsgesellschaft WTS Group Aktiengesellschaft Steuerberatungsgesellschaft

Information and communication services	
Microsoft Deutschland GmbH DB System GmbH Atos IT Solutions and Services GmbH Fiducia & GAD IT AG Software AG United Internet Media GmbH Computacenter AG & Co. oHG	Bechtle AG Finanz Informatik GmbH & Co. KG DATEV SAP SE 1&1 Versatel GmbH Lufthansa Systems GmbH & Co. KG Vodafone GmbH
Management and IT-consulting	
GfK SE Accenture GmbH McKinsey & Company Inc. msg group GmbH BearingPoint GmbH Sopra Steria GmbH CANCOM SE Materna GmbH Information & Communications	The Boston Consulting Group GmbH & Co. KG Intelligence AG Aareon AG GFT Technologies Capgemini Deutschland GmbH SQS Software Quality Systems AG Roland Berger GmbH Deloitte Consulting GmbH
Insurance	
Allianz SE R+V Versicherung AG Münchener Rückversicherungs-Gesellschaft AG Generali Versicherung AG HUK-COBURG Haftpflicht-Unterstützungs-Kasse kraftfahrender Beamter Deutschlands a.G. AXA Konzern AG Gothaer Versicherungsbank VVaG Nürnberger Lebensversicherung AG SV Sparkassenversicherung	ARAG SE WWK Lebensversicherung aG DEVK Deutsche Eisenbahn Versicherung Sach- und HUK-Versicherungsverein aG Betriebliche Sozialeinrichtung der Deutschen Bahn VHV Vereinigte Hannoversche Versicherung aG Continental Krankenversicherung aG HDI Haftpflichtverband der Deutschen Industrie VVaG Alte Leipziger Lebensversicherung aG Basler Versicherung AG