Assimilation and differentiation: A multilevel perspective on organizational and network change

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This paper builds on recently derived stochastic actor-oriented models (SAOMs) for the coevolution of one-mode and two-mode networks, and extends them to the analysis of how concurrent multilevel processes of (internal) organizational and (external) network change affect one another over time. New effects are presented that afford specification and identification of two apparently conflicting micro-relational mechanisms that jointly affect decisions to modify the portfolio of internal organizational activities. The first mechanism, assimilation, makes network partners more similar by facilitating the replication and diffusion of experience. The second mechanism, functional differentiation, operates to maintain and amplify differences between network partners by preventing or limiting internal organizational change. We illustrate the empirical value of the model in the context of data that we have collected on a regional community of hospital organizations connected by collaborative patient transfer relations observed over a period of seven years. We find that processes of social influence conveyed by network ties may lead both to similarity and differences among connected organizations. We discuss the implications of the results in the context of current research on interorganizational networks.

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1 Introduction

Formal organizations are composite entities characterized by hierarchical internal structures (March and Simon, 1958; Simon, 1996). Considering formal organizations as nodes in dynamic inter-organizational networks gives rise naturally to problems of change across multiple levels of action (Laumann et al., 1978). In interorganizational networks, the micro level is defined in terms of the portfolio of internal activities held by individual organizations. This portfolio is the result of conscious investment decisions in production capacity and of accumulation of productive resources (Cohen and Levinthal, 1990). Decisions taken at this level produce change in internal organizational structures. The macro level is defined in terms of the portfolio of network ties that organizations establish with partners in the hope to benefit from their resources, experience and knowledge (Beckman and Haunschild, 2002; Cohen and Levinthal, 1989). Decisions taken at this level produce change in network structures in which individual organizations are embedded. How are these two levels of action connected and how does change at one level affect change in the other? This question is relevant because one of the distinctive features of formal organizations is that they can reconfigure and change their internal structure while at the same time constructing networks of relations with other organizations (Padgett and Powell, 2012).

The aim of this paper is to bring recent advances in stochastic actor-oriented models (SAOMs) to bear on these fundamental questions in the context of an empirical analysis of interorganizational networks. Our work extends previous research by introducing for the first time a dynamic network model that supports joint representation of interdependent processes of change in internal organizational structure, and change in ties with network partners.

We represent internal organizational structure as a two-mode network that affiliates organizations to their internal activities. Organizations construct similarities and differences by changing individual ties in this network. We then reconstruct interorganizational networks on the basis of collaborative resource exchange relations. Organizations modify the structure of this network by establishing of abandoning relations with other organizations.

We identify two multilevel mechanisms linking internal organizational change to change in network ties between organizations. The first, assimilation, erodes the differences between connected organizations by facilitating the transfer of knowledge and experience. The second, functional differentiation, maintains the differences between connected organizations by stabilizing resource flows between partner organizations. The model we propose allows us to identify and examine these two multilevel influence mechanisms.

Extant studies have focused either on how organizations change their portfolio of network partners as a function of organizational characteristics (Beckman et al., 2004), or on how organizations change components of their internal structure as a function of characteristics of their network partners (Galaskiewicz and Wasserman, 1989). We are not aware of studies that have done both in the context of an explicit multilevel representation of concurrent processes of organization and network change. This is our main contribution in this paper.

We situate the empirical analysis in the context of patient transfer relations within a geographically bounded community of hospital organizations. We focus on patient transfer activities because the high degree of communication and coordination that this relation requires represent a reliable signal of cooperation between partner hospitals (Iwashyna et al., 2009; Lomi et al., 2014). On the basis of field work and data that we have collected, we analyze how hospitals manage their portfolio of network ties by changing (adding or dropping) relations with exchange partners, while at the same time changing their internal structure by adding or abandoning clinical activities. The analysis focuses on multilevel network mechanisms responsible for coupling these two processes of change. The specific advantage of this setting is that detailed information is available on patient transfer relations between hospitals and about their internal organizational structure. The setting we have selected is particularly useful for our purposes also because the substantial attention that health care authorities devote to ensure and measure quality of care delivered by hospitals produces data that are both reliable as well as publicly accessible.

2 Hypothesis Development

Extant research recognizes that an organization's position in the relevant interorganizational networks has consequential implications for its performance, productivity and innovative output (Ahuja, 2000; Shan et al., 1994). With very few exceptions (Paruchuri, 2010), little attention has been dedicated to how interorganizational networks affect the internal dynamics of organizational structure – and hence the actual capacity of organizations to generate desirable outcomes. Because organizations act as "knowledge repositories" (Argote and Ingram, 2000) it would seem natural to admit that their internal structure is influenced by external network ties through which information and knowledge resources flow (Powell et al., 1996; Rosenkopf and Almeida, 2003).

The paucity of research on this topic is surprising, but understandable as part of a more general problem. When organizations are considered as network nodes, they become embedded in dynamic multilevel structures connecting processes of internal organizational change and external network change (Padgett and Powell, 2012). Despite the extensive research on interorganizational networks accumulated during the last two decades (Gulati and Gargiulo, 1999) – and despite clear earlier warnings (Laumann et al., 1978; DiMaggio, 1986) – no study has fully recognized the multilevel implications of considering organizations as nodes in networks. In the typical study of interorganizational networks, multilevel issues are resolved by looking for intermediate levels of analysis between whole networks and individual organizations (Rowley et al., 2005). Therefore, an evident gap remains in our understanding of how internal organizational structures and external networks co-evolve. In this article we show how recent refinements of stochastic actor-oriented models (SAOMs) may facilitate a first step in the direction of filling this gap (Snijders et al., 2013).

When organizations are considered as network nodes, the lower ("micro") level is represented by the internal portfolio of production activities – the material, operational basis of organizational knowledge according to Cohen and Levinthal (1994). Change in organizational structures is driven by decisions to reconfigure the portfolio of network ties that affiliate organizations to their internal activities.

The higher ("macro") level is represented by the network of ties that organizations build to support their attempts to sample the experience of diverse partners (Beckman and Haunschild, 2002), and to control extramural resources (Cohen and Levinthal, 1994). Change in network ties is driven by decisions to reconfigure the portfolio of relations with exchange partners.

No systematic theoretical account exists of how these multilevel processes of change are connected and how they might affect one another. As a starting point, however, we can rely on one of the fundamental theoretical insights of institutional theories of organizational fields (DiMaggio, 1986) to identify the basic multilevel mechanisms involved. A fundamental tenet of institutional theories holds that interdependent organizations tend to become more similar in "structure" and "behavioral focus" because "a position of dependence leads to isomorphic change" (DiMaggio and Powell, 1983, p. 153). It is possible, therefore, that organizations connected by network ties, i.e., interdependent organizations, become more similar in terms of their internal activities and structures. This isomorphic change may be driven by multiple mimetic processes such as, for example, emulation, learning, influence or – in more generic terms – diffusion and contagion (Galaskiewicz and Wasserman, 1989; Strang and Soule, 1998). Whatever the underlying mechanism, the outcome will be that the portfolios of activities held by organizations connected by network ties will tend to become more similar over time.

Interorganizational relations are multidimensional and serve as *directed* channels for resource transfers. Directed flows of resources between organizations constitute imbalanced dependence relations. Reproducing the experience of partners may be a strategy to reduce this dependence. When interorganizational ties are directed, dependence reduction mechanisms operate thus more strongly for organizations that are transferring valuable resources to others. The sender organization, therefore, may try to reduce dependence and retain resources by reproducing the capacity of the receiver, i.e., by assimilating components of the receiver's internal structure. This argument is summarized in our first hypothesis.

Hypothesis 1. *In directed interorganizational networks, organizations transferring valuable resources to partners will attempt to reduce their dependence on exchange partners by assimilating components of their internal structure.*

Note that hypothesis one postulates a multilevel closure mechanism (Snijders et al., 2013) because it connects the presence of ties between organizations to change in internal organizational structures. The situation is represented, schematically, in the upper part of table 1 where black circles are organizations and dark red squares are components of organizational structure – or activities.

[Table 1 about here.]

At time 1 organization i transfers resources to j which holds activity k in its portfolio of internal activities. The arrow linking i to k in the second panel illustrates the tendency of *i* to reproduce the operational experience of *j* at time 2 – i.e., the tendency to assimilate components of *j*'s internal structure. The aggregate outcome of this assimilation mechanism will be structural isomorphism, or the tendency of interdependent organizations to become increasingly similar as predicted by DiMaggio and Powell (1983).

Are interdependent and hence interconnected organizations always similar? What limits the progressive assimilation of each others' experience? Extant research instructs us that complementarity is a strong driver of interorganizational relations (Gulati and Gargiulo, 1999; Rivera et al., 2010). Complementarity allows organizations to accomplish complex tasks together while reducing the opportunities for competition (Kogut, 1988). As Rowley et al. (2005) note, functional specialization reduces competitive tensions among partners and increases the stability of interorganizational relations. Organizations can thus profit from developing specialized portfolios of activities that are different from the activities of their partners. In particular, organizations that are not highly dependent on their network partners are more likely to follow the complementarity strategy.

On the basis of these considerations we would expect that organizations receiving valuable resources from partners will tend to establish and maintain complementary differences rather than trying to become more similar by reproducing the operational experience of partners. In this sense, maintaining distinctiveness may also be interpreted by partners as a signal of reliability and trustworthiness. Our second hypothesis summarizes this argument.

Hypothesis 2. *In directed interorganizational networks, organizations receiving valuable resources from partners will try to keep their internal structure distinct from that of sending partners.*

Hypothesis 2 postulates the presence of a multilevel differentiation mechanism at work to maintain and possibly amplify structural differences between interacting organizations. We have based this hypothesis on the principle of structural differentiation. As it was the case for hypothesis one, hypothesis two lends itself to a simple graphical representation. In the lower part of table 1, dark red squares are organizational activities and black circles are organizations.

At time 1 organization *i* receives resources from *j* which holds activity *k* in its portfolio of internal activities. The lack of connection between *i* and *k* at time 2 captures the tendency of *i* against assimilating components of *j*'s internal structure – i.e., a tendency against reproducing the operational experience of *j* (Cohen and Levinthal, 1994).

Considered jointly, hypotheses 1 and 2 imply that the presence of bonds of collaboration between two organizations might trigger both tendencies toward structural isomorphism as well as tendencies toward structural differentiation. In turn, these parallel tendencies toward assimilation and differentiation may be responsible for the recurrent empirical observation that organizations maintain networks of partners that contain both similar as well as dissimilar alters (Beckman et al., 2004; Powell et al., 2005; Sorenson and Stuart, 2008).

Both hypotheses are genuine multilevel hypotheses because they concern mechanisms that regulate how change at one level (internal organization) and change at another (external interorganizational networks) involve interdependent sets of decisions that pertain to different levels of action and structure.

In the next section we begin our discussion on the modeling framework that we need to develop to test these hypotheses and on the organizational setting that we will be using to illustrate the empirical value of the model.

3 A Dynamic Model for Multilevel Networks

We model changes of internal organizational structure (micro level changes) as part of a more general organizational change process that also implicates the dynamic level of interorganizational changes (macro level changes). The model addresses theoretical *multilevel network* mechanisms in which two levels (the micro and the macro level) co-evolve. In this paper, multilevel does not refer to nested data structures.

Internal organizational structure is described as a two-mode network that affiliates organizations to their internal activities. Organizations construct similarities and differences by changing individual ties in this network. Organizations are considered similar if they maintain the same internal activities. In the two-mode network representation, two organizational nodes will then be connected to the same node representing one type of internal activity. We then reconstruct interorganizational networks on the basis of collaborative resource exchange relations. Organizations modify the structure of this network by establishing or abandoning relations with other organizations.

We assume that changes in the two networks are the result of organizational decisions: organizations decide to modify the portfolio of collaborative network ties and the composition of their internal activities. These decisions on two levels are interdependent. We extend and apply novel stochastic actor-oriented models (SAOMs) for the co-evolution of a one-mode and a two-mode network (Snijders et al., 2013) that are capable of expressing this complex structure.

Formally, collaborative structures between organizations (for example, patient transfers between hospitals) at time t are described as a one-mode network with organizations i, j represented by rows and columns in a matrix $X(t) = (x(t)_{ij})$. Internal structure of organizations (for example, clinical activities) at time t are described as two-mode networks with organizations i represented by the rows and internal activities k by the columns in a matrix $Y(t) = (y(t)_{ik})$. To simplify the notation from now on we name the matrices x and y.

Changes in the two networks are triggered by actor-oriented decisions taken by the organizations (the *actors*). We assume that actors control both their outgoing collaboration ties and their affiliation with internal activities and that they can decide to change these structures at any point in time (the *agency* is on an actor-level). Timing and frequency of network changes are modeled as a Poisson process with equal rates for each actor (Snijders, 2005, sec. 8.1) which is not of focal interest in our analyses. Rather, we investigate the changes that are likely to be made given that an organization considers making a change in one of the two networks.

The preference structure of these changes is modeled by evaluation functions f^X and f^Y that express "characteristics of [actors'] personal networks toward which the actors seem to be attracted" (Snijders et al., 2013, p.268).

$$f_i^X(x,y) = \sum_k \beta_k^X s_{ki}^X(x,y) \tag{1}$$

$$f_i^Y(x,y) = \sum_k \beta_k^Y s_{ki}^Y(x,y) \tag{2}$$

Statistics $s_{ki}(x,y)$ represent these characteristics for changes in the networks x and y. For example, a statistic might evaluate the level of reciprocity in an actor's personal[1] collaboration network x after changing a network tie. Variable k identifies the statistic and i is the actor taking a decision to change either network x or y. Parameter β_k weights the k-th statistic and is subject to empirical estimation. When actors change their personal network they may face different options, for example, to create a reciprocating collaboration tie with a distant hospital or dropping a collaboration tie with a similar hospital. The probability of the different options is modeled as a multinomial choice probability with the evaluation functions being the linear cores. Let $x^{i \to j}$ w.l.o.g. be the network x after actor i changed the tie to j (added or dropped it) and $x^{i \to i} = x$. Let $\mathscr{R}_x$ ($\mathscr{R}_y$) be the set of "receiving" actors in the network (organizations in network x, internal activities in network y). Then, the probability of actor i making a particular tie change in network x (y) is defined as:

$$P(\text{change tie } i \to j \text{ in } x) = \frac{\exp\left(f_i^X(x^{i \to j}, y)\right)}{\sum_{h \in \mathscr{R}_x} \exp\left(f_i^X(x^{i \to h}, y)\right)} \tag{3}$$

$$P(\text{change tie } i \to k \text{ in } y) = \frac{\exp\left(f_i^Y(x, y^{i \to k})\right)}{\sum_{l \in \mathscr{R}_y} \exp\left(f_i^Y(x, y^{i \to l})\right)} \tag{4}$$

Note that changes in network x may depend on characteristics of network y and vice versa. Snijders et al. (2013, sec. A.2) provides more details on the mathematical model.

We rely on two classes of network-based mechanisms represented by a set of statistics $s_{ki}^X(x,y)$ and $s_{ki}^Y(x,y)$. The first class (one-mode network effects) regulates the creation and change of network ties in the interorganizational network x. For example, the reciprocity effect is included in the hospital model to account for the tendency of hospitals to reciprocate patient transfer relations. Partly, the decisions to change collaboration structures will be explained by the internal structure of a hospital (the two-mode network y). Table 2 provides the necessary information on this first class of effects. The dependent network tie (the one that is subject to change in equation 3) is indicated by a curly arrow. Organizations are represented by circles,

[1] "Personal" refers to the part of networks x or y that matters for i's decisions about changes. The shape and size of the relevant network part is defined by the complexity of the statistics in f. If, for example, only outdegree and the level of reciprocity matter for an actor's decision, then the personal network only incorporates those network dyads that this actor is part of.

internal activities by squares. Arrows represent ties in either the one- or two-mode network. Statistics $s_{ki}(x,y)$ are formulated according to the standards in Ripley et al. (2013); Snijders et al. (2013).

[Table 2 about here.]

The second class of mechanisms (two-mode network effects) regulates the affiliation of organizations to their internal activities. For example, the four-cycles effect is included in the hospital model to account for the tendency of hospitals to maintain portfolios of specialties that are similar to the portfolio of others. Table 3 provides essential information on this second class of effects. Effect 11 (*Receiving patients to similar specialties*) was newly developed for this study and allows us to distinguish collaboration relations that relate to sending resources (effect 10) from relations that relate to receiving resources (effect 11). Effects 10 and 11 are the two core effects regarding the hypotheses formulated in section 2.

[Table 3 about here.]

Of particular interest in this model are multilevel network effects which reflect the influence of relations in one network on changes in the other. We introduced the following three multilevel effects: effect 7 in table 2 (*Similar specialties to sending patients*), effect 10 (*Sending patients to similar specialties*) and effect 11 (*Receiving patients to similar specialties*) in table 3.

Further effect statistics that we use as control variables regarding organizational and relational covariates can be found in Ripley et al. (2013, p. 124–128).

4 Empirical Setting

We collected data on all patient transfers occurred between 2005 and 2011 among the 35 hospitals in Abruzzo, a geographic region in Southern Italy with a population of roughly 1,300,000 inhabitants distributed over approximately 4,200 square miles. Abruzzo is organized into four urban areas (Chieti, L'Aquila, Pescara, and Teramo), and further divided into 305 municipalities, none of which are major urban centers. In fact, only 10% of municipalities had more than 10,000 residents, 30% had fewer than 1,000 residents, and even the largest city (Pescara) had fewer than 120,000 residents during the study period.

The health system of Abruzzo is part of the Italian National Health Service (NHS), a public health system funded from general taxation that provides comprehensive health insurance coverage and uniform health benefits to all citizens and legal residents, throughout the country. The organization, financing, and provision of health care services in Abruzzo are entrusted to Local Health Units (LHUs), which serve populations of roughly equal size within their jurisdiction defined in terms of zip codes[2]. LHUs represent the natural markets from which

[2]Over the study period (2005-2011), the number of LHU reduced from six to four. In particular, four LHUs merged into two in 2009, thus resulting in a total of four LHUs covering the geographic areas of the main provinces of the Region (Chieti, L'Aquila, Pescara, and Teramo).

hospitals derive basic input resources – namely, patients and budgetary funds – and to which hospitals render their services. Our sample includes all the 13 private accredited hospitals and all the 22 public hospitals (including two university teaching hospitals) that provide acute care services in the region[3].

While it is increasingly common to emphasize the economic aspects of hospitals as organizations competing on price and quality for profitable patients (Gaynor and Vogt, 2003), hospitals differ from most conventional business organizations because hospitals operate in environments that are jointly technical and institutional (Scott and Meyer, 1991). As such, hospitals represent an almost ideal example of organizations whose economic performance and social legitimacy depend on their ability to collaborate with other hospitals (Lomi and Pallotti, 2012; Mascia and Di Vincenzo, 2011; Mascia et al., 2012).

Patient transfer is one of the most important forms of inter-hospital collaboration (Lee et al., 2011; Veinot et al., 2012; Iwashyna and Courey, 2011), and typically occurs via direct inter-hospital patient transfers whereby patients discharged from one ("sender") hospital are admitted to another ("recipient") hospital. To be sure, patient transfers are ostensibly intended to promote the patient's health: A transfer occurs when a hospital has patients with therapeutic needs for which it has constrained physical capacity available, or patients with complex pathologies for which it does not have adequate technologies or clinical competences, or patients with pathologies that may be treated more efficiently and effectively elsewhere. Patient transfers reflects underlying organizational decisions to involve a partner hospital in the search for a common solution to specific clinical or therapeutic problems.

In public health care systems such as the one we analyze, data on inter-hospital patient transfers are routinely collected for policy purposes to assess the geographical structure of demand for health care services, and the institutional coordination requirements that such structure imposes on hospitals (Ugolini, 2001). This offers very detailed information about inter-hospital patient transfers.

In our analysis, we concentrate specifically on the transfer of in-patients. In-patients are individuals who have already acquired the status of "admitted patient" and, therefore, who have consented to follow the clinical and therapeutic paths proposed by professional medical staff who are clinically responsible and legally liable for their conditions. This is an important qualification because individual patient transfer events induced by in-patient transfers are the outcome of organizational decisions over which patients have surrendered control at admission. Of course, patients retain the right to refuse transfer in the same way as they retain the right to refuse treatment. However, patients cannot choose where they will be transferred – a decision that remains a prerogative of the hospital.

The central argument that we develop in this paper involves a coupling between two distinct, yet interdependent organizational decisions. The first is the decision to share patients with a partner hospital. The second is the decision to change the composition of the portfolio of internal activities by adding or abandoning clinical activities. We argue that the second decision

[3]During the observation period the number of hospitals decreases from 35 to 30.

will most likely depend on the portfolio of internal activities of those hospitals that patients are shared with. Central to this argument is the assumption that the "direction" of patient transfers matters because economic resources as well as clinical information accompanying the patient can be considered valuable resources for hospitals.

Indeed, patients represent one the most important and vital resource for hospital organizations (Lomi and Pallotti, 2012). In the Italian National Health System financial resources are distributed among hospitals proportionally to the number of patients they treat. As in most public health care systems around the world, reimbursements and fees for services provided to hospitalized patients are determined according to a general Diagnosis-Related Group (DRG) system, whereby providers are compensated on the basis of the number and complexity of patients treated. As such, patient transfers between hospitals entail transfer of resources from one hospital to another. The most relevant support for this assumption comes from the fact that the reimbursement process for treatment of patients implies that the budget "follows" the patient. In other words, patients are assigned cash values for the care that those patients receive. These funds are lost by the sender hospital and accrue to the receiving hospital. Accordingly, receiving a patient is regarded as a direct source of funding for the hospital.

The decision to change the internal composition of organizational activities is particularly complex for public hospitals because these hospitals enjoy lower levels of autonomy. Public hospitals' investment and divestment decisions are typically subjected to institutional constraints imposed by public health authorities on the availability of financial, human and political resources. These constraints are somewhat weaker on private hospitals. While private hospitals tend to enjoy higher levels of managerial autonomy, they are typically subjected to the competitive constraints imposed by the market for health care services.

5 Research Design

5.1 Data

We collected information on dyadic relations defined in terms of patient transfers among all the 35 hospitals operating in the Abruzzo region. Using publicly available data on inter-hospital patient transfers, we constructed seven patient transfer matrices of size 35x35. Each matrix contains in each row (column) the sender (receiver) hospital, and in the intersection cells the number of patients transferred from the row to the column hospital. The matrices of patient transfer relations are asymmetric, since for any hospital in the sample the number of patients sent typically differs from the number of patients received. Because we are interested in longitudinal processes of establishing and dissolution of collaboration ties, rather than change in their intensity, we derived seven binary matrices by setting a tie to 1 if at least one patient transfer was observed. It is common that only a small number of patients is transferred between collaborating hospitals. Over seven years we observe 415 collaboration links with only one patient transfer within a year, 565 links with fewer than three transfers and 699 with fewer than five transfers. Inter-organizational collaboration agreements that regulate only a small number of patient transfers may potentially fluctuate between 0 and 1 when a dichotomization rule as the one above is applied. To rule out the effect of possible fluctuation on the SAOM results, we additionally conducted all dynamic analyses with dichotomization thresholds of three and five. The results turned out to be robust. Table 4 reports the main descriptive statistics of the collaboration networks that we analyze. The figures in the table 4 suggest that the density of the networks – i.e., the actual number of relations relative to the total number of possible relations – fluctuates between 0.11 and 0.17 with larger values after the dropout of hospitals with less collaboration ties in the last three waves.

[Table 4 about here.]

A visualization of the patient transfer network in Abruzzo in the first year of data collection is shown in figure 1.

[Figure 1 about here.]

Table 5 provides information on tie changes occurring in subsequent periods[4]. Stability between consecutive observations for the patient transfer network can be measured by Jaccard coefficients (Batagelj and Bren, 1995). Jaccard coefficients range between 0, if no tie is stable, and 1, if all ties stay the same (Snijders et al., 2010). The stability of the patient transfer networks is relatively high as revealed by Jaccard coefficients ranging between 0.45 and 0.52.

[Table 5 about here.]

We also collected detailed information on clinical activities performed within each hospital. Based on this information, we constructed seven (two-mode) matrices of hospitals by clinical activities. In the intersection cells, a 1 indicates that the row hospital contains the column activity, and 0 otherwise. A total of 45 activities were present over the seven-year period. On average, each hospital contains 11.4 activities (st.dev. 8.6). The minimum number of activities contained within a hospital in the sample is 1, while the maximum number is 32. Table 6 ranks the most 5 popular and the 3 least popular activities, together with the average number of hospitals containing them per year.

[Table 6 about here.]

Table 7 reports the main descriptive statistics of the (two-mode) hospitals-by-activities networks that we analyze. Most specialties are occupied by at least one hospital at a time.

[4] In the Table, $0 \to 0$ (null dyads) stands for the number of hospitals that do not collaborate at two consecutive time points, whereas $1 \to 1$ (stable dyads) is the number of hospitals collaborating at two consecutive time points. The other two transitions ($0 \to 1$ and $1 \to 0$) indicate the number of new partnerships and the number of dissolved partnerships over two consecutive time points, respectively.

[Table 7 about here.]

Finally, Table 8 reports the change statistics in the two-mode networks. The specialty affiliation network is more stable than the collaboration network. The distance between subsequent networks – the total sum of newly occupied and dissolved specialties – ranges between 19 and 81 per period.

[Table 8 about here.]

5.2 Variables and Measures

We control for a number of organization-specific attributes that may provide alternative explanations for the tendency of hospital organizations to change the internal structure or to share patients. We might suspect, for example, that larger hospitals have a higher activity level in the transfer network simply because they treat more patients, or that hospitals are more attractive as recipients if they have low occupancy (less crowding). We include the total number of staffed beds (*Size*) to control for the higher activity level of larger hospitals, and the average percentage of beds occupied in the preceding period (*Occupancy Rate*) to control for the effect of crowding. To control for the possibility that hospitals dealing with more complex cases are preferred recipients, we use the Case Mix index (Pettengill and Vertrees, 1982) as a measure of the average *Complexity* of the cases treated by a hospital.

We also control for features of particular dyads in the network that may affect the likelihood of transfers. For example, we expect that patients are transferred more frequently between hospitals that are closer in geographic space (Sorenson and Stuart, 2001). We thus control for *Distance* between each hospital to account for the joint effect of transportation costs and clinical risks inherent in the decision to transfer patients over long distances. We measure distance in driving minutes, rather than geographic distance in order to capture the various physical constraints that hospitals must consider in making transfer decisions (Abruzzo is a mountain region). Additionally, geographic and administrative reasons may make patient transfers more likely within rather than between Local Health Units (LHUs). We thus control for membership of partner hospitals in the *Same LHU*. We also control for the *Same Institutional Profile* of hospitals to rule out the possibility that different types of hospitals differ in their tendencies to send and receive patients[5]. To control for the effect of dependence on common resources for which hospitals compete (i.e., patients) we include the variable *Niche Overlap*, as conceptualized by Podolny et al. (1996) and as derived by Sohn (2001) specifically for

[5]Hospitals in the sample are classified according to three institutional categories, each comprising hospitals with similar legal form and ownership structure. The three institutional categories are: (1) LHU hospitals - which are publicly owned organizations, managed directly by the referent Local Health Unit (LHU), providing a wide range of secondary care services; (2) University polyclinics - which are linked to universities and provide highly specialized care (i.e., tertiary care), and (3) Private accredited hospitals - which are investor-owned organizations providing ambulatory, hospital care and/or diagnosis services through a contracting system with LHUs.

representing (spatial) competitive interdependence in a hospital dyad[6]. Further, we control for the tendency to choose specialties with a high in-degree (*Indegree popularity*). This variable models that some specialties generally attract more ties (see table 6). Partly, this ranking is determined by general market requirements and is not just an endogenous outcome of the dynamic process.

Table 9 reports the main descriptive statistics of the control covariates included in the empirical model specification.

[Table 9 about here.]

5.3 Dynamic Model Specifications

The dynamic approach that we develop allows us to control for a variety of structural effects (e.g., to test whether collaboration is likely to be reciprocated) and covariate-related effects (e.g., to test whether large hospitals are more likely to collaborate). Additionally, we test the extent to which the two sub processes (collaboration and change of internal structure) are interdependent. Given the complexity of a fully specified model we choose a step-wise model-building approach that allows to investigate the interdependence of different effects.

Model 1 is a base line model that only includes structural and covariate-related control variables but no multilevel effects (effects that express the interdependence between the two networks). The two sub models can, therefore, be interpreted as independent models of change in the two networks.

Model 2 includes all parameters of model 1 and, additionally, all three multilevel effects. The estimates indicate whether there is a general tendency of a tie in one network to increase the likelihood of tie occurrence in the other. In the sub model on collaboration dynamics, we test whether hospitals that are sharing many specialties are more likely to establish and maintain collaborative links. This effect is operationalized by effect 7 in table 2. In the sub model on specialty affiliation dynamics we test whether hospitals that are collaborating are more likely to become and remain similar. We distinguish between the directions of collaboration. Effect 10 and effect 11 from table 3 test whether hospitals that send patients to (10) or receive patients from (11) other hospitals are more likely to establish and maintain similar specialties.

Model 3 is similar to model 2 but distinguishes between the creation and maintenance of network ties for all three multilevel effects (effects 7, 10 and 11 in tables 2 and 3). In the macro level sub model, this allows us to understand whether the creation of collaborative relations with similar hospitals is different from the maintenance of such links. In the micro level sub

[6]Niche overlap among hospitals is measured as follows. For each year, patient discharges are aggregated to the zip code level to construct one patient origin-destination matrix $X = (x_{ik})$ with hospitals i being represented by rows and patient zip codes k by columns. In the Abruzzo Region there are 305 zip code areas. Niche overlap is hence computed as: $C_{ij} = \frac{\sum_k w_{ik} \min(x_{ik}, x_{jk})}{\sum_k w_{ik} x_{ik}}$ where $\min(x_{ik}, x_{jk})$ indicates the overlap (or "intersection") in patient pools between hospital i and hospital j in zip code k, and the weight w_{ik} indicates the relative number of patients who come from zip code k. Sohn (2001, equ. 5) explains the measure C_{ij} in more detail.

model, we can test whether the creation of internal specialties differs from the maintenance of internal specialties.

5.4 Model Estimation and Parameter Interpretation

Our model describes the circumstances under which hospitals take decisions to create, maintain or dissolve ties in two networks. The first part of the model describes changes in the network of collaboration ties (macro level), the second part of the model describes internal changes in the portfolio of clinical specialties (micro level). These changes are not directly observed but inferred from differences between annually collected network data (see tables 4, 5, 7 and 8). The SIENA estimation procedure simulates a large number of hospital decision chains (starting from the networks at the beginning of a period) that are likely to have generated an outcome similar to the one observed (the networks after a period). Rate parameters indicate the expected number of tie changes of one hospital in a period. We conduct maximum likelihood estimation to determine the parameters. It is explained in more detail in (Ripley et al., 2013, sec. 6.5).

Parameters are interpreted in the context of decisions of hospitals about network changes. If a hospital considers changing a collaboration network tie, the actually changed tie will be influenced by a number of parameters. For example, hospitals may strive for reciprocity with an estimated parameter with value $\hat{\beta}_k = 2$ (see equation 1 and effect 2 in table 2). Then we can conclude that an average hospital will be – all other conditions being equal – $\frac{e^{2\cdot 1}}{e^{2\cdot 0}} =\approx 7.4$ times more likely to create a tie with a hospital j that it is receiving patients from $(s^X_{2i}(x^{i\to j}, y) = 1)$ than with a hospital h that it is not receiving patients from $((s^X_{2i}(x^{i\to h}, y) = 0)$. This value follows from the odds of the two probabilities. The denominator of equation 3 cancels out.

6 Results

Results of the estimations are presented in table 10. It consists of two parts: The upper half includes the macro-level estimates of the *patient transfer dynamics* (parameters 1–32), the lower part includes the micro-level estimates of the *specialty affiliation dynamics* (parameters 33–48). Each part consists of six change rate parameters (1–6, 33–38) and a number of effects that are related to network structures or covariates. Three models were estimated as discussed in section 5.3. The multilevel parameters (including parameters 43–48 that relate to the hypotheses in section 2) are highlighted gray.

[Table 10 about here.]

We find some support for both our hypotheses. First, hospitals transferring valuable resources to partners by sending patients will attempt to reduce their dependence by reproducing components of the internal structure of the receiving partner (Assimilation Hypothesis 1). Second, hospitals receiving valuable resources from partners by receiving patients will try to keep their internal structure distinct from that of exchange partners (Differentiation Hypothesis 2).

The tendency to change internal structures based on the internal structure of collaborators is captured by effects 43 (*Sending patients to similar specialties*) and 46 (*Receiving patients to similar specialties*) in model 2. In particular, these effects compare changes in the *number of common clinical specialties* between collaborators when changing the portfolio of internal specialties. The direction of collaboration is taken into account. The two effects are depicted in table 3 as number 10 and 11. Effect 43 (number 10 in table 3) is *positive* and expresses the tendency of hospitals to *reproduce and maintain* the internal structure of partners in case the hospital sends patients to that partner. Effect 46 (number 12 in table 3) is *negative* and expresses the tendency of hospitals to *remain distinct* from a partner in case the hospital receives patients from that partner. The absolute values of the estimates can roughly be interpreted as follows.

First, all else being equal a hospital is 19% more likely to add a new clinical specialty to its portfolio if this specialty is maintained by a hospital it is *sending patients* to ($e^{0.17} = 1.19$). The baseline probability is the probability of choosing a specialty that is not maintained by a receiving partner hospital. This explanation follows from the estimate of effect 43 (*Sending patients to similar specialties*) which is 0.17. Second, a hospital in the similar situation that is the *receiver* of patients is 13% more likely to choose a specialty that is not maintained by the partner hospital ($1/e^{-0.12} = 1.13$) rather than assimilating to the partner's structure. This follows from the estimate of effect 46 (*Receiving patients to similar specialties*) which is -0.12. The baseline probability is the probability of choosing a specialty that is not maintained by a sending partner hospital. When distinguishing creation of internal structure from its maintenance in model 3, we can see that the differentiation mechanisms (hypothesis 2) seems to work through maintaining differences (the significant maintenance effect 47) rather than through newly adding distinct portfolio items (the creation effect 48 is insignificant). We cannot make a similar statement regarding the assimilation mechanisms (hypothesis 1). Both the creation and maintenance effects (44 and 45) are insignificant.

An additional notable result is that similarity regarding internal activities seems to facilitate collaboration. Similar organizations are more likely to establish collaboration relations. The tendency to collaborate with similar partners is captured by effects 30 (*Similar specialties to sending patients*). It represents the general tendency to create, maintain and avoid dissolving ties with similar partners. It is small but significant on a 90% confidence level. In model 3, this effect is replaced by separate creation and maintenance effects. We find evidence (creation effect 32) that similarity facilitates the creation of new ties. We can not answer whether these ties are more or less stable (maintenance effect 31) than collaboration ties between dissimilar organizations as the corresponding effect is not significant.

There is a number of further notable parameters in the model. Effect 40 (*Four-cycles*) reveals the tendency of hospitals to choose specialties that are also chosen by other hospitals with a similar internal structure. This effect measures the tendency of hospitals to adopt specialties that are maintained by others with which the hospital has other specialties in common (see effect 9 in table 3). Effect 41 (*Specialty indegree popularity*) measures the tendency to choose and maintain specialties that are commonly chosen. This relates to the descriptives in table 6.

The other effects in the models are either rate parameters, structural or covariate-related control variables and are only selectively discussed. For example, in the patient transfer process we control for the size of the sending and receiving hospital: Effects 18–19 have positive estimates in model 1 which indicates that large hospitals are associated with a higher probability of sending and receiving patients. In models 2 and 3, these parameters loose significance. We further test whether sending and receiving hospitals are similar regarding size: Effect 20 (*Size similarity*) has a negative estimate in model 3 which shows that patients are rather shared between hospitals of different sizes. In the specialty affiliation process we control for hospital size as well (effect 42 – *Size ego*) and find that large hospitals are more likely to maintain a high number of specialties. An example of a dyadic covariate effect is the distance in minutes (effect 14 – *Distance in minutes*). It shows that hospitals that are close regarding travel time are more likely to collaborate. Some parameter estimates and their standard errors have been multiplied by ten to improve readability (as indicated in the results table 10).

7 Discussion and Conclusions

We started this paper by observing that the lack of appropriate models has so far prevented students of organizations to understand organizational and network change as coupled multi-level processes (Padgett and Powell, 2012). In this paper we have argued that developing a dynamic multilevel understanding of change is an unavoidable consequence of considering organizations as network nodes.

Developing a multilevel understanding of organizations as network nodes hinges on our capacity to represent how organizations reconfigure their internal structure while at the same time constructing and changing their relations with partners. This representation problem is of general theoretical relevance and goes much beyond its contextual instantiation that we have examined in this paper. As Padgett et al. (2003, p. 843) suggestively put it:

> "The production and distribution of goods by firms are only half of what is accomplished in markets. Firms also are produced and transformed through goods passing through them. This transformation is not just a matter of profits. Skills and the core competencies that define firms are developed and maintained through 'learning by doing' and other learning processes that are triggered by exchange among firms".

"Learning by doing" is a side effect of investment in production activities. It follows decisions about where to locate organizational boundaries in the space of potential production activities (Cohen and Levinthal, 1994; Williamson, 1991). The "other learning processes triggered by exchange" are side effects of network ties that organizations establish with partners in an attempt to access their experience and resources (Beckman and Haunschild, 2002).

In this paper we have contributed to this theoretical debate in two ways. First, we have linked these two levels of action and combined them into a multilevel model of organization and network change. Second, we have shown how the underlying mechanisms of change – not their side effects – may be analyzed directly and linked to relevant data by extending existing SAOMs for the coevolution of one-mode and two-mode networks originally derived by Snijders et al. (2013).

Our analysis reveals that processes of assimilation as well as differentiation are simultaneously at work to shape the organizational and network structures. According to the former process (assimilation), asymmetric resource exchange makes partners organizations progressively more similar. According to the latter (differentiation), asymmetric resource exchange maintains and amplifies structural differentiation. One important aspect of our results is that these opposite processes are concurrent, i.e., they work at the same time. We think that this result may help to extend and qualify the classic insight of institutional theories of organizations by revealing the presence of network-based mechanisms that limit the progressive tendency toward structural isomorphism in interorganizational fields (DiMaggio and Powell, 1983). This result is also important because it provides a realistically complex understanding of dependence and influence relations as capable of producing and maintaining both similarities, as well as differences between organizations connected by network ties.

In their current state of development, the models for multilevel networks we have proposed contain elements of innovation, but also a number of limitations. Four in particular deserve mention in this concluding section as each limitation indicates clear directions for future research. First, our model forced us to limit the discussion to qualitative organizational change. But organizational change is both episodic and continuous (March, 1981). Extending SAOMs for two-mode networks by incorporating an objective function for *continuous change* is at the moment beyond our reach but promising first steps are being made in this direction. Second, our model forced us to aggregate observed flows of resources (patients) into network ties and to restrict our analysis to the binary architecture of the network. Current developments of relational event models (Butts, 2008; Brandes et al., 2009; Stadtfeld and Geyer-Schulz, 2011; Stadtfeld, 2012) suggest ways in which this current limitation of the model may be alleviated and possibly resolved. Third, we have limited our multilevel representation to two levels: internal organizational structure (micro) and interorganizational field (macro). While this distinction was empirically meaningful in the context we have examined, it is easy to think of more complex situations that require the specification of additional levels (Padgett and Powell, 2012). Future developments in multilevel SAOMs will have to raise to the challenge of addressing these issues directly in concrete empirical contexts (Snijders and Koskinen, 2012). Fourth, as it is typical for empirical studies, the results of the current study have clear scope conditions. For example, we make no claim that our findings hold for any kind of tie regardless of its content. We have simply shown that the effects we postulate operate on tie that have an explicit cost. The extent to which the same mechanisms operate on ties generated by relations in which costs are implicit (like, for example, information exchange) remains an open question that future research should clarify.

It may be appropriate to conclude our discussion by calling attention on the fact that the empirical setting that we have examined is characterized by a number of distinctive institutional idiosyncrasies which limit the generality of the results we reported. Only systematic replication may establish the generality of our models and the empirical scope of our results. However, we believe the problem we have addressed is sufficiently general to deserve additional attention in future research on how interorganizational networks and organizational structures affect one another and coevolve. The potential solution we have offered is similarly general.

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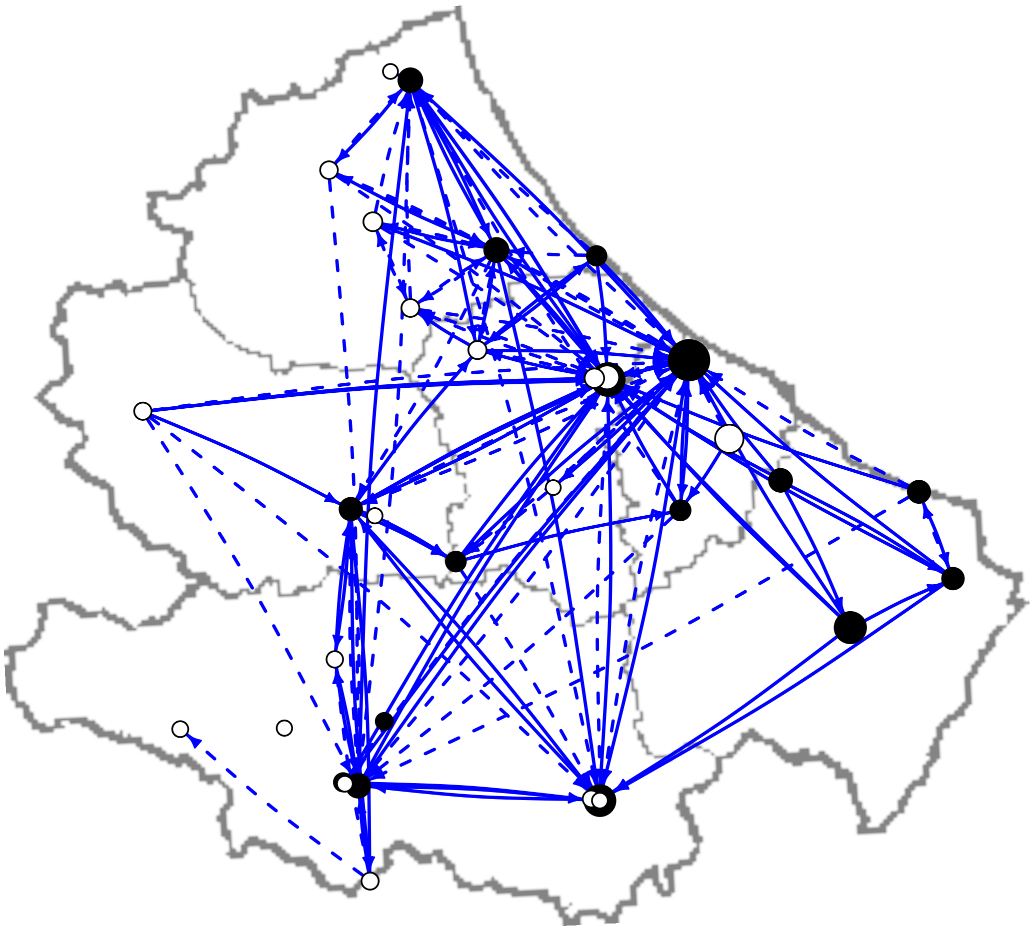


Figure 1: *Visualization of the patient transfer network in Abruzzo in the first year of data collection. The circles represent 35 hospitals. The size differences are proportional to the differences in the number of beds that hospitals maintains. Hospitals with at least ten specialties are drawn black, hospitals with fewer specialties are white. If a hospital sends patients to another hospital with which it shares less than 30% of the specialties, the corresponding arrow is dashed, otherwise it is solid. The position of the nodes represents their approximate spatial location within the Abruzzo region (the map in the background).*

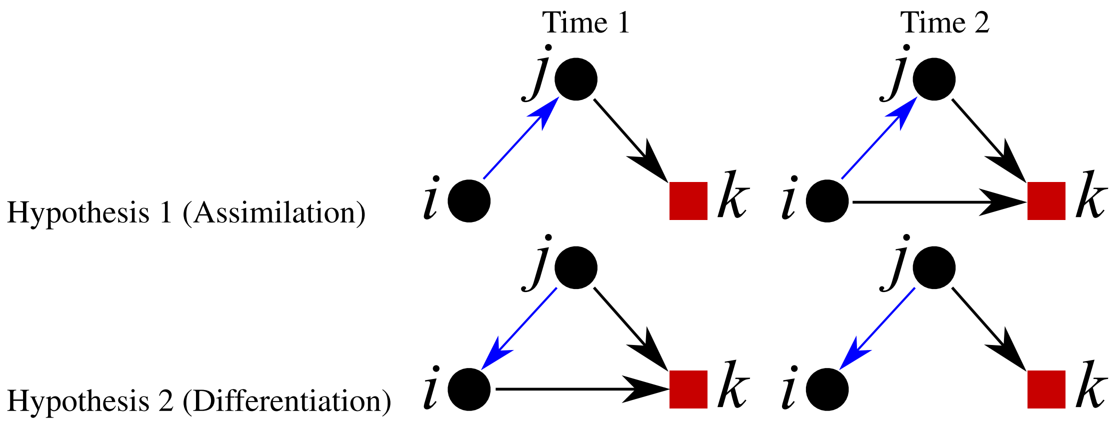


Table 1: *Illustration of the mechanisms underlying hypotheses 1 and 2. Organizations are represented by circles (i and j), organizational activity by a square (k). An arrow to k indicates that an organization pursues the activity. An arrow between two organizations indicates collaboration in which the direction of the arrow represents flow of resources. If both organizations connect with k, they are considered similar.*

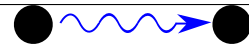
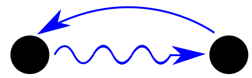
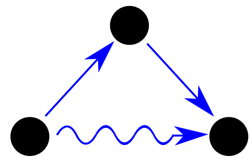
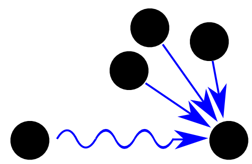
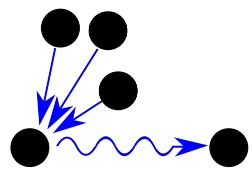
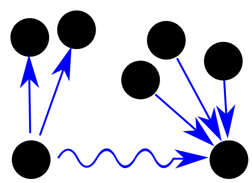
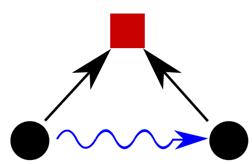
No.	Name	Figure	Equation
1	Outdegree		$s^X_{1i}(x,y) = \sum_j x_{ij} = x_{i+}$
2	Reciprocity		$s^X_{2i}(x,y) = \sum_j x_{ij} x_{ji}$
3	Transitivity		$s^X_{3i}(x,y) = \sum_{j,h} x_{ih} x_{hj} x_{ij}$
4	Indegree popularity		$s^X_{4i}(x,y) = \sum_j x_{ij} x_{j+}$
5	Indegree activity		$s^X_{5i}(x,y) = x_{i+} \sum_j x_{ji} = x_{i+} x_{+i}$
6	Out-in degree assortativity		$s^X_{6i}(x,y) = \sum_j x_{ij} x^2_{i+} x^2_{+j}$
7	Similar specialties to sending patients		$s^X_{7i}(x,y) = \sum_{j,k} x_{ij} y_{ik} y_{jk}$

Table 2: *Structural effects describing the change of directed ties between organizations (macro level). Circles represent organizations, squares internal activities. The changing network tie is depicted as a curly arrow connecting actors i and j. Other arrows represent ties in either the one-mode or the two-mode network. Two organization nodes connected to one square indicate maintenance of similar activities.*

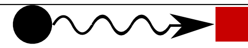
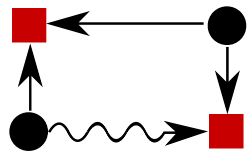
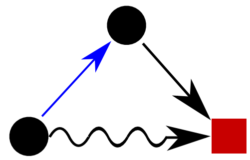
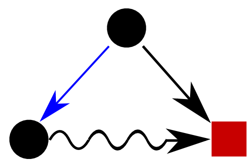
No.	Name	Figure	Equation
8	Outdegree		$s^Y_{8i}(x,y) = \sum_k y_{ik} = y_{i+}$
9	Four-cycles		$s^Y_{9i}(x,y) = \sum_{j,k,l} y_{ik} y_{il} y_{jk} y_{jl}$
10	Sending patients to similar specialties		$s^Y_{10;i}(x,y) = \sum_{j,k} x_{ij} y_{jk} y_{ik}$
11	Receiving patients to similar specialties		$s^Y_{11;i}(x,y) = \sum_{j,k} x_{ji} y_{jk} y_{ik}$

Table 3: *Structural effects describing the change of internal structure of organizations (micro level). Circles represent organizations, squares internal activities. The changing network tie is depicted as a curly arrow connecting actor i and node j. Other arrows represent ties in either the one-mode or the two-mode network. Two organization nodes connected to one square represents their maintenance of similar activities.*

	Wave						
	1	2	3	4	5	6	7
N hospitals	35	35	35	35	33	31	30
Density	0.11	0.10	0.12	0.12	0.15	0.17	0.17
Avg. degree	3.8	3.3	3.9	4.0	4.7	5.0	5.0
N ties	133	114	137	139	156	155	150

Table 4: *Descriptives of the dichotomized collaboration networks in the seven data collection waves (2005 – 2011).*

	Period					
	1-2	2-3	3-4	4-5	5-6	6-7
$0 \rightarrow 0$	1028	1020	1004	987	911	850
$0 \rightarrow 1$	29	56	49	64	55	49
$1 \rightarrow 0$	48	33	47	47	56	54
$1 \rightarrow 1$	85	81	90	92	100	101
Distance	77	89	96	111	111	103
Jaccard	0.52	0.48	0.48	0.45	0.47	0.50

Table 5: *Descriptives of the collaboration changes in the periods between subsequent data collection waves.*

Rank	Specialization	Avg. occurrence
1	Surgery	28.86
2	General medicine	27.86
3	Orthopaedics and trauma	22.71
4	Obstetrics and gynaecology	19.29
5	Cardiology	18.86
...	...	...
43	Spinal unit	0.71
44	Dentistry and dental	0.43
45	Immunology	0.29

Table 6: *Most and least popular specialties.*

	Wave						
	1	2	3	4	5	6	7
N specializations	43	44	45	42	42	42	42
Density	0.26	0.26	0.26	0.22	0.23	0.23	0.22
Avg. degree	11.5	11.6	11.7	10.1	10.6	10.4	10.1
N ties	404	405	409	354	370	363	353

Table 7: *Descriptives of the specialty two-mode networks in the seven data collection waves (2005 – 2011).*

	Period					
	1-2	2-3	3-4	4-5	5-6	6-7
$0 \rightarrow 0$	1196	1195	1188	1221	1140	1057
$0 \rightarrow 1$	10	10	13	35	10	10
$1 \rightarrow 0$	9	6	68	19	17	20
$1 \rightarrow 1$	395	399	341	335	353	343
Distance	19	16	81	54	27	30
Jaccard	0.95	0.96	0.81	0.86	0.93	0.92

Table 8: *Descriptives of the two-mode network changes in the periods between subsequent data collection waves.*

Variable name	Mean	SD	Min.	Max
Size	153.1	136.2	20	661
Occupancy Rate	0.73	0.2	0.05	1.77
Complexity	0.95	0.1	0.09	1.42
Distance	69.0	28.8	2	146
Same Institutional Profile	0.5	0.5	0	1
Same LHU	0.2	0.4	0	1
Niche Overlap	0.24	0.3	0.0	1.0

Table 9: *Descriptives of control variables*

		Model 1		Model 2		Model 3	
		est.	s.e.	est.	s.e.	est.	s.e.
	Macro-level: Patient transfers						
1	Period 1	5.47	(1.06)	5.51	(1.12)	5.39	(0.96)
2	Period 2	6.44	(1.58)	6.73	(1.23)	6.44	(1.18)
3	Period 3	7.89	(1.91)	8.47	(1.67)	8.42	(3.78)
4	Period 4	11.32	(3.54)	11.69	(5.07)	11.59	(2.48)
5	Period 5	6.42	(0.98)	6.42	(0.86)	6.37	(0.84)
6	Period 6	5.61	(0.69)	5.60	(0.81)	5.61	(0.69)
7	Outdegree	-3.69^{***}	(0.24)	-3.80^{***}	(0.27)	-3.76^{***}	(0.25)
8	Reciprocity	0.72^{***}	(0.12)	0.69^{***}	(0.12)	0.69^{***}	(0.12)
9	Transitivity	0.13^{**}	(0.04)	0.13^{**}	(0.04)	0.13^{**}	(0.04)
10	Three-cycles	-0.07	(0.05)	$-0.08^{\dagger}$	(0.05)	$-0.08^{\dagger}$	(0.05)
11	Indegree popularity (x10)	0.23	(0.15)	0.24	(0.16)	$0.25^{\dagger}$	(0.15)
12	Indegree activity (x10)	0.03	(0.22)	0.09	(0.23)	0.08	(0.21)
13	Out-in degree assortativity	0.16^{***}	(0.04)	0.15^{***}	(0.04)	0.15^{***}	(0.04)
14	Distance in minutes (x10)	-0.13^{***}	(0.02)	-0.13^{***}	(0.02)	-0.13^{***}	(0.02)
15	Niche overlap	-0.05	(0.19)	0.01	(0.19)	-0.01	(0.19)
16	Same institutional profile	0.22^{**}	(0.08)	0.21^{**}	(0.08)	0.21^{*}	(0.09)
17	Same LHU	1.08^{***}	(0.11)	1.08^{***}	(0.11)	1.08^{***}	(0.11)
18	Size alter	0.17^{***}	(0.05)	$0.12^{\dagger}$	(0.06)	$0.11^{\dagger}$	(0.06)
19	Size ego	0.12^{*}	(0.06)	0.05	(0.07)	0.06	(0.07)
20	Size similarity	-0.27	(0.26)	$-0.56^{\dagger}$	(0.31)	-0.57^{*}	(0.29)
21	Size: higher to lower	-0.14	(0.13)	-0.12	(0.15)	-0.12	(0.13)
22	Complexity alter	$0.54^{\dagger}$	(0.29)	$0.52^{\dagger}$	(0.28)	$0.49^{\dagger}$	(0.28)
23	Complexity ego	0.10	(0.30)	0.08	(0.29)	0.13	(0.30)
24	Complexity similarity	0.44	(0.37)	0.46	(0.38)	0.46	(0.36)
25	Complexity: higher to lower	-0.14	(0.11)	-0.14	(0.11)	-0.15	(0.11)
26	Occupancy rate alter (x10)	-0.01	(0.03)	-0.01	(0.03)	-0.01	(0.03)
27	Occupancy rate ego (x10)	$0.04^{\dagger}$	(0.02)	$0.04^{\dagger}$	(0.02)	$0.04^{\dagger}$	(0.02)
28	Occupancy rate similarity (x10)	5.67	(3.85)	5.92	(3.95)	5.89	(4.04)
29	Occupancy rate: higher to lower (x10)	$-2.29^{\dagger}$	(1.18)	$-2.24^{\dagger}$	(1.22)	-2.35^{*}	(1.18)
30	Similar specialties to sending patients			$0.02^{\dagger}$	(0.01)		
31	(=) Similar specialties to sending patients					0.01	(0.02)
32	(+) Similar specialties to sending patients					0.04^{*}	(0.02)
	Micro-level: Specialty affiliations						
33	Period 1	0.59	(0.14)	0.59	(0.14)	0.59	(0.14)
34	Period 2	0.49	(0.12)	0.49	(0.13)	0.49	(0.13)
35	Period 3	2.83	(0.35)	2.82	(0.34)	2.84	(0.35)
36	Period 4	1.81	(0.26)	1.80	(0.27)	1.82	(0.27)
37	Period 5	0.75	(0.16)	0.75	(0.16)	0.74	(0.16)
38	Period 6	1.05	(0.19)	1.04	(0.19)	1.04	(0.19)
39	Outdegree	-2.34^{***}	(0.15)	-2.47^{***}	(0.17)	-2.44^{***}	(0.17)
40	Four-cycles (x10)	0.16^{***}	(0.02)	0.13^{***}	(0.03)	0.14^{***}	(0.03)
41	Indegree popularity	0.04^{**}	(0.01)	0.05^{**}	(0.01)	0.04^{**}	(0.01)
42	Size ego	0.36^{***}	(0.06)	0.44^{***}	(0.08)	0.40^{***}	(0.09)
43	Sending patients to similar specialties			$0.17^{\dagger}$	(0.09)		
44	(=) Sending patients to similar specialties					0.19	(0.15)
45	(+) Sending patients to similar specialties					0.06	(0.13)
46	Receiving patients to similar specialties			$-0.12^{\dagger}$	(0.07)		
47	(=) Receiving patients to similar specialties					-0.26^{*}	(0.10)
48	(+) Receiving patients to similar specialties					0.07	(0.11)

Table 10: *Results of three dynamic models. Multilevel parameters are highlighted gray. Some estimates and standard errors have been multiplied by ten for better readability; confidence levels:* $\dagger$*:* $p < 0.1$*,* **:* $p < 0.05$*,* ***:* $p < 0.01$*,* ****:* $p < 0.001$*; standard errors are in parentheses. Maintenance effects and creation effects are marked with (=) and (+).*