THE CONCEPT OF SIMILARITY IN INTERORGANISATIONAL NETWORKS: AN EMPIRICAL APPLICATION IN HEALTHCARE

ANNA PIAZZA

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Declaration

I certify that the work contained in the thesis, or any part of it, has not been accepted in substance for any previous degree awarded to me, and is not concurrently being submitted for any degree other than that of (Doctor of Philosophy) which has been studied at the University of Greenwich, London, UK.

I also declare that the work contained in this thesis is the result of my own investigations, except where otherwise identified and acknowledged by references. I further declare that no aspects of the contents of this thesis are the outcome of any form of research misconduct.

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Student Name: Anna Piazza

Student Signature:

Date: 16.03.2020

First Supervisor's Name: Francesca Pallotti

First Supervisor's Signature:

Date: 16.03.2020

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ABSTRACT

In organisational research, the term “similarity” is frequently used to describe the principle of bonding among organisations, i.e. how organisations come together, thus making the concept as the main factors that leads to the creation and maintenance of inter-organisational relation among organisations. Examples of research that focuses on the mechanisms of similarity are becoming increasingly common in inter-organisational network research. In today’s business environments, organisations do not operate in isolation; rather, they embed themselves in complex sets of relations with other organisations, usually with the aim of exchanging resources and coordinating their activities for the solution of a common problem. But what makes collaboration and coordination among organisations more likely to occur? And, what are the effects of collaboration and coordination for organisational behaviour and performance? One way to address these questions is to unfold the concept of similarity as a multifaceted concept, underlying various social processes operating in inter-organisational networks. The current work builds on the literature on the antecedents and consequences of inter-organisational networks and adds a focus on the concepts of performance similarity (Chapter 4), social similarity (Chapter 5), and resources complementarity (Chapter 6) to explain the dynamics of inter-organisational networks. The three essays draw on organisation and network theories to investigate under what conditions social network structures emerge and influence organisational behaviour. This work shows that (i) Similarity in organisational performance is contingent on how peer effects operate at various levels in inter-organisational networks. (ii) Collaboration among organisations is a function of both geographical proximity and social similarity, whereby the effect of geographical proximity is contingent on the position that organisations occupy within network structures. (iii) The effect of resources complementary is contingent on the geographical location of organisations. The opportunity to address empirically my research questions is provided by longitudinal data collected on patient transfer relations within an Italian community of hospital organisations from 2006 to 2009. The results of the empirical analyses contribute to advance our understanding of social selection (i.e., network theory), social influence (i.e., theory of networks), and co-evolution (i.e., network theory of networks) mechanisms in explaining the dynamics of inter-organisational networks.

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Chapter 1: Introduction

The term "inter-organisational relations" (IOR) refers to any type of social relationships among and between organisations, usually with the aim of exchanging resources and coordinating their activities for the solution of a common problem. Thus far, different forms of IOR have been theoretically and empirically investigated (see Parmigiani & Rivera-Santos, 2011 for a recent review) along with their effects on organisational behaviour.

However, two fundamental questions remain unanswered: What makes collaboration and coordination among organisations more likely to occur? What are the effects of collaboration and coordination for organisational behaviour and performance?

One way to address to these questions is to look at the social network analysis as a lens to investigate organisations. A network consists of a set of social actors (referred to as nodes or vertices) that are connected through relationships (referred to as links or edges). Thus, a relational or network approach takes into account not only a set of social actors and their attributes but also the relationships among them. In his theoretical paper, Powell (1990) makes a distinction between markets, hierarchies, and networks, as alternative forms of interactions that are present in transaction cost economics. Markets occur outside the formal organisations, where price and contracts define the normative basis for relationships. In contrast, hierarchies occur inside the organisations, where the form of division of labour defines the normative basis for relationships. Networks work differently from both markets and hierarchies. When nodes in a network are represented by organisations, the network is called an organisational network. The extant organisational literature suggests that organisations establish collaborative relationships to access extramural resources that they do not have internally (Gulati & Gargiulo, 1999; Powell, Koput, & Smith-Doerr, 1996). This leads to the sharing of experience and knowledge by organisations across organisational boundaries.

The existing literature also suggests that organisations encountering each other simultaneously in multiple markets develop collaborative arrangements aimed at easing the competitive pressure experienced by them in these markets (Gulati, 2007). Irrespective of whether they are aimed at enhancing collaboration or reducing competition, IOR brings a number of benefits to the interconnected organisations. In order to understand how inter-organisational networks (IONs) benefit organisations, scholars have looked at the formation of network ties, i.e. the probability of two organisations to form a relationship; and the consequence of network ties,

i.e. how the position of an organisation within the network influences the diffusion of information through the network relationships (Borgatti *et al.*, 2009).

The increasing recognition that IORs influence organisation behaviour also requires an investigation of how and why IONs change in the first place (Majchrzak, Jarvenpaa, & Bagherzadeh, 2015; Knoben, Oerlemans, & Rutten, 2006). Knoben, Oerlemans, & Rutten, (2006) reviewed the literature on the dynamics of IONs. They reviewed the literature to compare i) the role of change in the analysis (independent *vs.* dependent variables) and ii) the manner in which the change is conceptualised (incremental *vs.* radical change and dyadic *vs.* network change). They concluded that despite the availability of studies that explore the formation and endurance of dyadic relationships, network evolution, and the effects of changes in the network structure, there is a need to explore the process through which networks evolve and change.

In the studies on the dynamics of IOR, there is an on-going debate on what constitutes similarity in organisational studies (Snijders and Lomi, 2019). Similarity is often used as synonym in four different ways: first, it has been attached to the mechanism of homophily which refers to the creation of network ties among similar organisations through share the same attribute (McPherson *et al., 2011*). Second, it has been linked to the concept of social proximity which refers to how organisations that are relationally close to each other are more likely to create ties (Boschma, 2005). Third, it has been attached to the mechanism of complementarity which refers to the combination of different attributes that generate value for the relationship (Rivera *et al., 2010*; Pfeffer & Salancik, 1978). Finally, it has been linked to the mechanism of homogeneity/ contagion in terms of organisational behaviour explaining the consequences of network ties where organisations become homogenous by adopting to the social environment (Borgatti *et al.*, 2009). However, looking at similarity as a synonym does not capture the entirely meaning of it, in fact, thus making the inter-organisational network field fragmented (Bergenholtz & Waldstrom, 2011) and the main gap is to no looking at similarity as a multidimensional concept that including different level of analysis as recently suggested by (Lomi & Snijeders, 2019). In line with this idea, my dissertation looks at the dynamics of IOR by considering the multifaceted dimensions of similarity.

1.1 Unfolding the concept of similarity in IONs: a theoretical foreword

In organisational studies, thus far, the network paradigm has been used to explain a variety of phenomena, such as performance, innovation, and group membership (Kilduff & Brass, 2010;

Brass, Galaskiewicz, Greve, & Tsai, 2004). The idea that organisations are embedded in networks of social relationships with other organisations has been at the centre of research interest across several disciplines, including management, economics, and sociology. Since 2000, the number of publications per year on organisational networks has grown exponentially (Halevy, Halali, & Zlatev, 2019; Borgatti, Brass, & Halgin, 2014; Phelps, Heidl, & Wadhwa, 2012). Although each discipline has its own reasons for analysing organisational/social phenomena, there is on-going debate on what the core ideas that characterise the network approach in organisations are. Indeed, criticism and confusion arise from the following fundamental question: Is a social network analysis a simple set of analytical tools and measures, or can it be considered a theoretical perspective? (Borgatti, Brass and Halgin, 2014). This question has led to the labelling of social network analysis as an 'umbrella term' that stretches across different disciplines (Kilduff and Brass, 2010). Scholars have rejected this criticism by clarifying social network analysis as a theory and developing a research programme that includes a core of ideas to understand the antecedents and the consequences of organisational networks (Kilduff and Brass, 2010; Borgatti and Halgin, 2011).

Considering the network paradigm, Borgatti & Halgin, (2011) distinguished between 'theory of networks' and 'network theory'. The network theory investigates how the network structure affects the organisational outcomes and performance. In contrast, the theory of networks investigates how and why a network structure is established. In essence, the network theory examines the consequences of network relationships, while the theory of networks examines the antecedents of these network relationships. However, these two perspectives can coexist in what has been called the 'network theory of networks', where the outcome of network relationships becomes an input for the formation of networks. The network theory of networks can be considered a bond model of a situation when both independent and dependent variables feature network properties. This perspective is also linked to the recent developments in network modelling that emphasise the co-evolutionary process where network properties co-evolve with network outcomes (Snijders and Lomi, 2019).

A discussion of bonding in networks allows us to consider the concept of similarity. Similarity has been used in many empirical studies to unfold the social processes in IOR (Rivera et al., 2010; Mizruchi & Marquis, 2006). Similarity is thus a multifaceted concept that underlines the mechanism of bonding among social actors, such as the idea that social actors have or form relationships with similar others (Snijders and Lomi, 2019). This bonding mechanism is similar to the old concept of solidarity proposed by Durkheim (1933). In the Division of Labour in

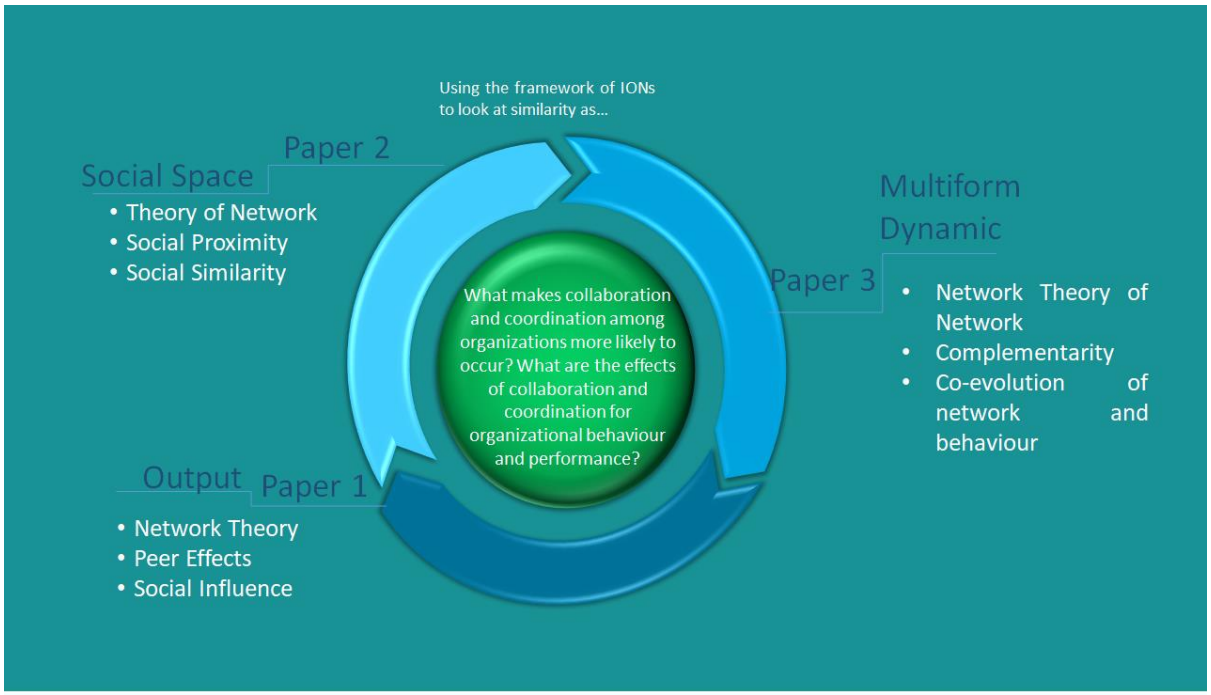
Society, Durkheim, (1933) stated that the interdependence among social actors is based on the pattern of social interactions among them. The idea that social interactions bind social actors together is considered the primary source for solidarity. He distinguished two different forms of solidarity. The first is mechanical solidarity which is based on the similarity among social actors (i.e. sharing values or attributes), and the second is organic solidarity which is based on the dissimilarity among social actors. Therefore, social actors are functionally connected by combining these two forms of solidarity. Each social actor is composed of different independent and complementary elements that lead to an interdependency among the social actors. This interconnection generates a similarity, whereby social actors are dependent on each other.

Bonding is one of the mechanisms behind the popular concept of similarity. Snijders & Lomi, (2019) argued that similarity captures a broad range of mechanisms reflecting the manner in which social actors (organisations in my case) come together. The basic mechanism is homophily, which is the tendency to form ties with others that are similar along relevant characteristics such as the attributes of social actors. Beyond homophily, there is attachment conformity, which is the preference to form relationships with others whose characteristics are in line with the established social norms. When this dimension is measured in IONs, it is observed that there is a modification of behaviour aligned with the norms. Aspiration is the preference to be connected with others with characteristics 'for which high values are generally found attractive' (Snijders & Lomi, 2019:3). A part of this dimension is sociability, which is the tendency of social actors with high values on a particular attribute to form more ties. Finally, complementarity is the combination of attributes that are valuable to organisations. In other words, it is the tendency to form relationships with others who are different with respect to certain specific characteristics. Snijders & Lomi (2019:2) reported the use of different dimensions of similarity 'depending on which units are being compared for the assessment of similarity'.

This conceptualisation of similarity as a bonding mechanism that consists of different dimensions provides the basis for the extension of similarity. Given the compositional nature of organisations as composite social agents, this dissertation adopts the suggestions of Snijders & Lomi (2019) and considers similarity as a multifaceted dimension in three important ways, i.e. (i) output, ii) social space, and iii) multiform dynamics.

Figure 1 shows how similarity is conceptualized in this dissertation

Figure 1: Conceptualization of similarity



Network theory: Similarity as output

Snijders & Lomi (2019) argued that one face of the attachment conformity is related to the 'adjustment of behaviour toward normative values' (2019:3). This dimension has been used to explain the consequences of IONs underlining the idea that some factors are channelled through network relationships from one node to another and, in turn, modify the behaviour of the social actors. In IONs, this is called the social influence or contagious or diffusion. Social influence is the process by which 'outside influences' affect the social actors' behaviour (Im, Mason and Houston, 2007). A peer effect is the process by which social actors 'make behaviour changes to be consistent with their peer network' (Valente & Pitts, 2017:4.3). Factors that generate a behavioural change are material resources, such as money, or symbolic resources, such as norm conformity, ideas, and social learning (Borgatti *et al.*, 2009). As a result of being influenced, social actors become progressively more similar in their behaviour orientation and outcomes. This topic has also been investigated in economics research, where it is often referred to as peer effects. Peer effects are defined as the associations between the outcomes of social actors who interact with each other (Bramoullé, Djebbari and Fortin, 2009) whereby a variation in a social actor's behaviour is associated with a strictly local form of dependence linking pairs of social

actors. However, the dependence among these dyadic relationships embed the social actors into broader IONs wherein peer effects operate (Haveman and Nonnemaker, 2000). Therefore, by integrating economics research with ION research, I propose that peer effects are seen as mechanisms that lead to the social influence process. This process is a possible outcome generated by the existence of peer effects to the extent to which two connected social actors are likely to behave similarly. Peer effects are likely to not be homogenous involving the transition from a local to a global dependency structure. Discussing the consequences in IORs and taking the concept of similarity as an output allow us to consider how the related mechanisms lead to similarities in behaviours among the connected social actors.

This was addressed in the first empirical study of this dissertation, which explored peer effects as the associations between outcomes (Bramoullé, Djebbari and Fortin, 2009). I investigated peer effects at multiple network levels and analysed which competing mechanisms at different levels might be responsible for observing the behavioural similarities among organisations. In this study, the dyadic relationships, network subgroups, and network positions within the entire network corresponded to the different levels of the analysis.

This study contributes to diverse streams of research, such as economics and social networks, thus investigating the consequences of network relationships. The presented evidence demonstrates that the persistence of similarities in performance is contingent on how organisations are embedded in the IONs through which the peer effects operate.

Theory of network: Similarity as social space

Similarity can also be understood by focusing on the attributes of the social actors. In IONs, this principle of similarity attraction is operationalised through homophily: the tendency to form relationships with those who are similar to themselves in terms of the relevant characteristics (McPherson, Smith-Lovin and Cook, 2001). In addition, social actors who are geographically close are more likely to establish network relationships (Rivera, Soderstrom and Uzzi, 2010). In both IONs and economics geography studies emphasise that being closer in the spatial and relational spaces encourage the establishment of network relationships and reduce the costs associated with resource transfers (Knoben and Oerlemans, 2006; Brass, 2011). Spatial space is typically associated with the notion of geographic proximity, i.e. the absolute or relative distance between the social actors, while relational space is typically associated with the notion of social proximity (Hansen, 2015). Social proximity is defined ‘in

terms of socially embedded relations between agents at the micro-level'(Boschma, 2005:66) and interpreted relationally as the degree of personal acquaintance (Uzzi, 1996). Therefore, social actors 'who prefer socially similar relationships should be more likely to take advantage of an opportunity to develop a strong tie with a social similar contact' (Reagans, 2011).

This malleability of social similarity is important to the construction of similarity as a social space, whereas the actual similarity is a function of occupying the same network positions in the entire network. In my conception of social similarity, social actors exchange their resources through a 'path' in the social space composed of indirect relationships between and among the network positions of the social actors. This means that social actors that occupy similar network positions are more likely to exchange their resources even if they are distant in the physical space, because they move through the social space. Social similarity takes place when social actors are not directly connected to each other; it occurs as a result of being similar in the relational profile. Therefore, separating the concept of social similarity from social proximity expands it significantly, as it can capture how social similarity can be represented by having the same relational profile with the same social actors, consequently connecting with the same social actors and leading to the formation of network relationships, even if they are distant in the social space.

This was addressed in the second empirical study of this dissertation, which explored the role of physical and social similarity in the inter-organisational collaboration networks. I investigated how social similarity amplified or reduced the effect that physical proximity had on the inter-organisational exchange relationships. In particular, I addressed how social similarity moderated the formation of collaborative relationships between physically distant organisations. I hypothesised that physical proximity and social similarity were important factors that affected the probability to exchange resources: organisations initiated and maintained collaborative relationships with those that were physically proximate and occupied the same network positions within the network as a whole. I also suggested that the positive effect that social similarity had on collaborative relationship increased with an increase in the physical proximity.

This study contributes to the stream of research that investigates the antecedents of network relationships by highlighting the interplay between geographical proximity and social similarity and by using positional similarity as a measure of social similarity. The presented

evidence demonstrates that the effect of physical proximity is contingent on the positions that organisations occupy within networks.

Network theory of networks: Similarity as multiform dynamic

The concept of similarity is often contrasted and compared with the concept of complementarity, which acts as an important driver for partner selection decisions. The concept of complementarity is generally defined as the dissimilarity along relevant attributes, whereby the relationships with dissimilar partners 'are complementary to their own and relevant to solving a particular problem' (Rivera et al., 2010:96). As such, complementary partners are 'those who are able to provide those task-related skills and resources that are necessary to fill the capability gaps of the focal firms' (Soda & Furlotti, 2017:353).

Building on the idea that social actors form relationships with others that are similar with respect to the same attributes, it is also evident that social actors form relationships with others that are dissimilar along different attributes. It is therefore likely to expand the concept of similarity as a multiform dynamic. The core idea is that social actors over time enhance their portfolio of internal resources (i.e. activities) by establishing the network relationships with the relevant partners simultaneously. In the case of multiform similarity, similarity is captured on the basis of the internal resources (i.e. activities) possessed by the social actors. The social actors express the preferential tendency to form relationships with both similar and dissimilar partners, sharing similarities on one dimension and dissimilarities on the other dimensions. Therefore, multiform similarity arises from the balance of (not) overlapping both similar and different attributes to extract value from their relationships. Thus, similarity is dynamic, because as the internal composition of the internal resources changes, the similarity between partners changes. In this sense, similarity can be extended to include the dynamic interplay between similar and dissimilar attributes, which leads to the consideration of the resources complementarity in IONs. Multiform dynamic similarity clarifies how social actors manage their interdependence between their internal resources and the external resources by having a *core of complementarity resources* and thus impacts the way these social actors construct their social network of relationships with their partners.

This was addressed in the third empirical study of this dissertation, which explored how networks emerged from social interactions with similar and dissimilar partners that over time shaped the enduring patterns of collaboration among organisations. Organisational scholars have broadly accepted the idea that partner selection decisions are driven by the considerations

of similar and dissimilar potential partners along the relevant dimensions, including resources complementarity. Recently, Furlotti & Soda (2018; 2017) distinguished between depth complementarity, which is the overlap of the same types of resources held by organisations, and scope complementarity, which is the overlap of different types of resources held by organisations. In this study, I adopted the distinction between scope and depth resources complementarity to understand whether partners were chosen on the basis of their physical location or whether they are chosen on the basis of how their organisational characteristics fit the organisational needs. In doing so, in this study, I specified the antecedents of the social network dynamics by using a stochastic-oriented model (SAOM) that linked the change in the internal composition of resources to the change in the networks of relationships among organisations. The longitudinal design and the analytical approach allowed me to represent the co-evolution thinking between organisational and network structures.

This study contributes to the stream of research that investigates the network theory of networks by highlighting how organisational characteristics and structural effects shape the dynamics of collaboration within inter-organisational communities.

1.2 Overview of the dissertation

The rest of this dissertation is structured as follows. Chapter 2 provides an overview of the theories and current research in inter-organisational field that informed my research and presents the gaps in the literature and focus of my research. Chapter 3 provides a background to the empirical setting and the data used by all the three independent and self-contained papers. Chapters 4, 5, 6 are the three specific empirical studies of the dissertation and look at the multidimensional concept of similarity from output, positional space and multiform dynamic perspectives respectively. Chapter 7 concludes the dissertation by highlighting research implications, contribution, limitation, and propose further directions that have the potential to advance the understanding of collaboration in healthcare system. The structure of this dissertation is summarized in figure 2:

Figure 2: Thesis Structure

1.3 Summary

This dissertation contributes to the investigation of inter-organisational collaborative relationships that evolve in different ways. This dissertation focuses on the concepts of similarity and complementarity, which contribute to the process of how IOR form and maintain over time and how this influences organisational behaviour (Chapters 4, 5, and 6). More specifically, Chapter 4 discusses the consequences of IONs by using the concept of peer effects as the correlation between outcomes. The findings of this study also have important

implications for policymakers in designing policies aimed at increasing the performance of organisations at the system level by making strategic choice based on the ability to structure their network in terms of "with whom they are connected to".

Chapter 5 discusses the antecedents of IONs by using the concept of social similarity and how it moderates the effect of geographical distance on the strength of collaboration. The findings reported here have implications for policymakers in designing policies that account to identify proximate partners and create collaboration across organisational boundaries in order to improve the level of healthcare services in different geographical areas. Chapter 6 looks at the effect of resources complementary on the dynamics of collaborative relationships among organisations, by using the different dimensions of resources complementarity, i.e. depth and scope complementarity while taken into account the geographical location of organisation. The reported findings point out the importance of designing policies aimed at managing collaboration and exploiting resources and capabilities held by collaborative partners in order to improve the allocation of different resources and to reduce the costs of healthcare services. Finally, responding to a renewed interest in the dynamics of IONs (Snijders and Lomi, 2019; Valente and Pitts, 2017;), I applied an econometrics model (Chapters 4 and 5) and a stochastic actor-based model (Chapter 6) for analysing the organisational networks within a healthcare delivery system.

From a relational perspective, the healthcare delivery system can be seen as a network: a system of relationships among interdependent social actors (e.g. hospitals or healthcare organisations in general) collaborating with each other for the benefit of the patients. Collaboration in healthcare may take various forms, such as strategic alliances, hospitals groups, joint training programmes for the hospital staff, and technology sharing. One form of collaboration that has received increased attention over the last few years is patient transfer, also known as patient sharing, involving the transfer of patients between partner hospitals (Lomi and Pallotti, 2012). Patient transfers are decisions taken by hospitals to involve other hospitals in the joint solution of a medical problem; here, the hospitals are free to select which hospital to choose to transfer a patient to. In making this choice, hospitals coordinate their activities to provide a continuum of care to the patients. Moreover, patient transfer relationships lead to financial outcomes, because revenue is linked to the patient flow. An understanding of the network may lead policy makers to consider new interventions for the improvement of the quality of care and, consequently, the efficiency level of the system.

Chapter 2: Literature Review

In the past few decades, work on inter-organisational relations (IORs) has grown considerably (Cropper *et al.*, 2008; Bergenholtz and Waldstrøm, 2011). Research on inter-organisational networks focuses on relationships between and among organisations. Inter-organisational collaboration among organisations is one of the most common forms of inter-organisational relations that has been studied in many empirical settings (Powell *et al.*, 2005; Whittington, Owen-Smith and Powell, 2009; Kitts *et al.*, 2017).

This section provides an overview of theories and current research in inter-organisational field that are used to inform my research. However, a more detailed discussion of the theoretical background that informs the three specific papers will be discussed in each of the chapters which are structured as independent and self-contained studies. The rest of this chapter is structured as follows. The first section describes the concept of organisations as composite social agents in inter-organisational networks. The second section discusses how inter-organisational relations have been investigated in the literature. The third section describes the antecedents and consequences of IOR. The fourth section emphasizes the multilevel perspective of inter-organisational networks. The fifth section provides an overview of extant research discussing inter-organisational networks in the healthcare field. Finally, this chapter concludes by identifying gaps in the literature that this research aims to fill.

2.1 Organisations as composite social agents

"*To every definite number of elements there corresponds in accordance with the purpose and spirit of their combination, a sociological form, an organisation, firmness of texture, relation of the whole to the parts"* (Simmel, 1902:34)

Sociologist George Simmel raised this fundamental statement in 1902. This was one of the first attempts to describe the compositional nature of organisations and reawaken the curiosity of organisational scholars towards the nature of social groups. Organisations are more than a collection of individuals. They are the sum of aggregate individuals' actions whose mission, goals and culture are created through the interactions of these actions. These roles and tasks take the form of a social division of labour regulated by coordinated activities between individuals (Durkheim, 1983) that support decision-making process within organisations.

By extension, organisations can be viewed as "*composite social agents*". Organisations are "*composite agents*" because they are the sum of aggregate individual's actions. Defining organisations as "*social agents*" means that organisations take decisions (Stadtfeld *et al.*, 2016). Organisations are seen as active agents that choose to change their internal organisational structure; thereby actively shaping the portfolio of network partners and making decision of it. By combining these two aspects and using a relational perspective, organisations can be seen as composite social agents characterized by two different yet interrelated features: first, internal organisational structure is represented by the set of organisational activities (Lomi and Stadtfeld, 2014). This subset of activities constitutes the internal portfolio that organisations hold, where resources are allocated following investment decision aimed at developing organisational capacities. Once a portfolio of activities is created, however, the internal organisational structure can change in response to patterns of resource availability. The possibility of organisations to change is based on the need to access resources that they do not have internally leading organisations to develop exchange relations with others. The development of these relations may depend on the set of activities possessed by organisation. This leads to the creation of portfolio of network partners (Stadtfeld *et al.*, 2016). The internal organisational structure (i.e. portfolio of activities) and inter-organisational networks (portfolio of network partners) coevolve: the portfolio of organisational activities contribute to relations formation and the resulting networks, in turn, influence organisations (Hollway *et al.*, 2017). Change in the internal organisational structure, in turn, influence their actions (Amati *et al.*, 2019).

2.2 Inter-organisational networks

In their classical essays, Laumann, Galaskiewicz, & Marsden, (1978) and DiMaggio, (1986) raised the problem of how organisations that act as composite social agents enter as a node in inter-organisational networks stating that an issue pertinent to node definition arises because a corporate actor is composed of individuals who are affiliated with multiple roles (Laumann, Galaskiewicz and Marsden, 1978). This problem is associated with the "micro and macro" perspectives highlighted before. The micro-dimension refers to those internal characteristics of organisations, such as the portfolio of activities that organisation hold. The macro-dimension refers to external networks in which organisations are embedded. Bringing together these two dimensions helps shed light on how relationships among organisations are established and the

relational mechanisms through which inter-organisational networks (IONs) are formed, maintained and changed (Stadtfeld *et al.*, 2016; Tranmer, Pallotti and Lomi, 2016).

In the past few decades, research on inter-organisational networks (IONs) has led to the accumulation of a relevant stock of knowledge. Inter-organisational networks refer to any kind of relationships between and among organisations. Inter-organisational relations (IORs) come to exist in various forms such as alliance, joint ventures, supply agreements, licensing co-branding, franchising, cross-sector partnership, networks, trade associations and consortia (Parmigiani and Rivera-Santos, 2011). These relations can be defined as "cooperative relationships between a focal organisation and one or more other organisations to share or exchange resources with the goal of improved performance" (xi: 1109). Studies adopting an I-O framework include those on strategic alliances (McCutcheon and Stuart, 2000); interlocking directorates (Mizruchi, 1996); joint ventures (Pfeffer and Nowak, 1976); collaborative relations (Powell, Koput and Smith-Doerr, 1996). IORs have been explained from two theoretical perspectives: organisational economics and organisation theories as suggested by Parmigiani & Rivera-Santos (2011). Within organisational economics, Parmigiani & Rivera-Santos, (2011) identify three theoretical perspectives that have been employed to investigate the existence of IONs: (i) transaction cost economics where organisations are seen as an accumulation of transactions (Williamson, 1985). Transactions define the costs of market versus hierarchy-based governance. (ii) Resource-based view which organisations create IORs to get complementary resources, where organisation are seen as sum of resources and capabilities. (iii) Agency theory where inter-organisational relations occur between principals and agents where ownership and control are separated. Inter-organisational relations are considered strategic decisions made by managers (i.e. agents) and these decisions affect shareholders (i.e. principals). The authors conclude that organisational economics describes the formation of IONs "when it is more efficient for a firm to conduct an activity through a close partner relationship than either on its own or through the market. The focus is on creating an appropriate governance structure, obtaining complementary resources, and aligning incentives among partners" (Parmigiani & Rivera-Santos, 2011:114).

Within the organisational theories, Parmigiani & Rivera-Santos (2011) identify fours theoretical lens that have been used to explain the existence of inter-organisational relations: the first is resource dependence theory which focuses on how organisations can cope with environmental uncertainty by getting access to resources that are controlled by others (Pfeffer and Nowak, 1976; Hillman, Withers and Collins, 2009). The second theoretical lens is

stakeholder theory that stresses on the selection of partners, i.e. influential stakeholders in order to manage uncertainty. The third is neo- institutionalism theory (DiMaggio and Powell, 1983) that emphasises on how organisations that are related to each other tend, over time to become progressively more similar in behavioural orientation, outcome and performance. Organisations can be influenced by three different forces that have been identified by institutional researchers, such as coercive, normative and mimetic (DiMaggio and Powell, 1983). Coercive isomorphism refers to political influence and organisational legitimacy including regulation and accreditation processes. Normative isomorphism refers to cultural values promoted by professions. Mimetic isomorphism refers to social pressures that lead organisation to imitate their successful peers. Frumkin & Galaskiewicz (2004) find that these three forces can easily overlap influencing organisational characteristics in various ways. However, extant literature highlights the fact that mimetic forces predominate in explaining organisational behaviour within inter-organisational networks. For example, Pallotti, Tubaro, & Lomi, (2015) emphasize how organisational behaviour is driven by mimetic pressures that lead organisations to imitate each other and hence, assimilate the behaviour of other organisations. The fourth perspective is social network analysis that focuses on the position of organisations within the network structures. It also looks at how organisations are embedded on the network of relations and how these patterns of relations constrain and enable organisation behaviour (Borgatti and Foster, 2003; Kilduff and Tsai, 2003). In summary, organisational theories stress on the relations among partners due to the fact organisations are embedded in a social structures. Legitimacy, status and reputation are important factors in the formation of relations among organisations. On the other hand, the endurance of such relations gives to organisations the possibility to reduce dependency and uncertainty.

The network approach is one of the theoretical lens that organisational scholars have used to study inter-organisational networks (Bergenholtz and Waldstrøm, 2011). Studies on inter-organisational networks involve three different units of analyses: (i) ego level involves relations among the focal organisation (ego) and its neighbourhood (alters); (ii) dyadic level involves relations between two organisations; (iii) whole networks refers to the pattern and characteristics of the whole inter-organisational network. Two network approaches have represented an important component in traditional studies on inter-organisational networks, such as positional and relational (Mizruchi, 1993; Mizruchi and Galaskiewicz, 1993). Positional approach examines relations by looking at the way two social actors occupy a position within the network as a whole although they do not necessarily interact with each

other, i.e. structural equivalence (White, Boorman and Breiger, 1976). For example, Galaskiewicz & Burt, (1991) find that structurally equivalent organisations are more likely to perform similarly even if they are not directly connected to each other. Relational approach examines relations by looking at how social actors interact with each other, i.e. cohesion (Marsden and Friedkin, 1994).

Beyond these two approaches, Zaheer, Gözübüyük, & Milanov (2010) identify four theoretical mechanisms that have been used by researches in different empirical contexts. The first looks at the network as resource access, where network are considered as important source of resources and capabilities. Resources stem from the characteristics of relations, from the structure of ego-networks and its alters' characteristics. Information is passed through strong and weak relations among organisations (Paris Granovetter, 1973). The second mechanism zooms at network as a source of trust, where network enables trust about the potential partners (Uzzi, 1996). Higher closure are more likely to generate higher level of trust (Coleman, 1988). For example, higher level of trust reduces costs and risks associated with the transfer of resources (Beamish and Lupton, 2009). The third mechanism describes network as a source of power and control, where network are seen to increase and constrain the power of the nodes. For example, resources dependency theory has been linked to these studies (Pfeffer & Salancik, 2003; Mizruchi, 1989). Other examples of theories are structural perspective where smaller organisations can reduce the power of big organisation by getting other organisation into the network (Bae and Insead, 2004) structural holes where organisations that occupy structural holes have more power and control to other organisations as their position enables them to strategically play off one organisations against another (Burt, 1992). The fourth describes networks as signalling mechanisms, where networks are seen as signs or pipes and prisms where network relations have material (pipes) and symbolic / interpretive lenses (prisms) (Podolny, 2001). For example, Stuart, Hoang, & Hybels, (1999) show how the creation of inter-organisational relations with a large pharmaceutical organisation is considered as a sign of quality for a new biotechnology organisation.

The application of these different mechanisms on inter-organisational networks also involves the understanding of how and why networks change and evolve (Knoben, Oerlemans and Rutten, 2006). Change is defined as 'variation in the underlying pattern of relationships that bind a given set of actors' (ix: 391). The authors review the literature by comparing (i) the role of change in the analysis (independent versus dependent variable) and (ii) the manner in which change is conceptualized (incremental versus radical change and dyadic versus network

change). Knoben et al. (2006) suggest three different group of studies that investigate change in IO- network literature: first group of papers stresses on the formation or termination of dyadic relations (i.e. causes of radical dyadic change), where studies on termination of dyadic relations are limited and secondly contradictory. The second group of paper involves studies on network evolution (i.e. causes of radical change in network structure, where studies explain how and why exogenous causes turn into critical event due to the ripple effect on the network as a whole. The third group of paper includes studies on consequences of changes in network structure for organisational outcomes, where few studies explain the impact of network structures on performance. The authors conclude 'in spite of the existing studies on the subject, very little is known about radical change in network structures' (Knoben, Oerlemans and Rutten, 2006).

However, one of the main issues in the IO-network literature is the use of various methodological approaches to explain organisational phenomena (Bergenholtz & Waldstrøm, 2011; Zaheer et al., 2010; Oliver & Ebers, 1998). In a literature review, Oliver & Ebers, (1998:549) pointed out 'the growth in the number of these studies seemingly does not ensure a clear accumulation of knowledge or even conceptual consolidation'. They noted that inter-organisational networks have been studied from different theoretical perspective leading to the fragmentation of the field. Based on Oliver & Ebers' findings (1998), Bergenholtz & Waldstrøm, (2011) review the literature to map different methodological approaches in the field of inter-organisational networks. Their review is based on whether social network analysis is applied as kind of network structure, level and unit of analysis, qualitative and quantitative methods; measurements include multiplex and valued relational data. They find that even if studies on inter-organisational networks have grown exponentially and use sophisticated methods, there is still less studies that explain organisational performance by using longitudinal design, multiplex data and whole network conceptualization. They conclude: 'no uniform approach exists and given the need to focus on institutional aspects, this will constitute a significant obstacle for de-fragmenting the field of inter-organisational network studies' (Bergenholtz & Waldstrøm, 2011:554).

To summarize what has been done in inter-organisational networks field, table 1 reports the main review papers selected using key-word search on google scholar are "inter-organisational relations" literature review" and "network". These five papers are the most cited papers.

Table 1: The five cited literature review paper on IONs

Author (s)	Publication year	Time period of analysis	Aim
Oliver & Ebers	1998	1980-1996	Investigation of linkages among and configurations of core theories and concept on inter-organisational relations and networks
Knoben et al.,	2006	1984-2005	Investigation of longitudinal inter-organisational networks studies – Studies on change in network structure overtime
Provan, Fish, & Sydow	2007	1985-2005	Investigation of studies on inter-organisational networks at whole networks
Bergenholtz & Waldstrøm	2011	1997-2008	Investigation of inter-organisational networks studies and applied methodologies
Parmigiani & Rivera-Santos	2011	2000-2010	Investigation of inter-organisational relations studies and applied theories – meta-review

To make sense of inter-organisational network theorizing in organisational theory, Borgatti & Halgin (2011) distinguish network theory, theory of networks, and network theory of networks in order to explain the mechanisms. Therefore, the next subsections will consider the mechanisms of IONs.

2.3 Antecedents and Consequences of IONs: Mechanisms

In a recent paper, Borgatti & Halgin (2011) distinguish two analytical domains: *theory of network* and *network theory*. *Theory of network* explores why and how network structures come to exist in the first place. *Network theory* refers to the mechanisms that come along with network structures to explain organisational outcomes, such as performance. In other words, while *network theory* stresses on the consequences of social network structures, the *theory of network* investigates the antecedents of social network structures.

Within the first domain, Rivera, Soderstrom, & Uzzi (2010) identify three 'distinct yet intimately interwoven' (ix:93) theoretical perspectives that explain the formation and evolution of inter-organisational relations. The first theoretical perspective is the assortative perspective which focuses on how similarities and differences among social actors influence network formation. Supporting this perspective, recent studies indicate that organisational characteristics, such as size, are associated with the structure and dynamics of inter-organisational relations (Powell *et al.*, 2005; Brass, 2011). In particular, mechanism that has been linked to social network structures and their dynamics is homophily; the tendency to create relations with similar others (McPherson, Smith-Lovin and Cook, 2001). For example, using data on semiconductor organisations, Stuart (1998) finds that organisations that are similar in their technologies are more prone to collaborate in order to avoid any duplication as "organisations are better able to evaluate and internalize the know-know of technologically similar firms" (1998:672). Another mechanism that has been attached to this perspective is heterophily: tendency to form relations with dissimilar others in terms of resources, capabilities that organisations held (Rivera, Soderstrom and Uzzi, 2010). Diversity allows organisations to collaborate with partners that are complementary to their own in order to fill the capability gaps of the focal organisation (Soda and Furlotti, 2017). For example, using data on the biotechnology sector, Powell et al. (2005) find that organisations increase their collaborations with diverse partners whereby new resources are channelled and combined. Using data on venture capital firms, Sorenson & Stuart (2008) find that organisations are more likely to collaborate with dissimilar partners that come from different specialization industries. The second perspective is relational perspective which investigates the role of existing patterns of collaboration and network positions as a driver for the creation of relationships among social actors. Studies on this perspective emphasize the importance of dyadic processes, i.e. reciprocity (Doreian and Mrvar, 1996), or repetition (Kossinets & Watts, 2006; Gulati & Gargiulo, 1999), but also how brokerage and cluster impact the formation of relations (Burt, Kilduff and Tasselli, 2013), and also how past collaboration impact subsequent network formations and transformations (Gulati, 1995). The last perspective is proximity, which highlights location and space, as well as time dimensions. Proximity perspective highlights the importance of space (i.e. physical) which generates opportunities to interact between organisations and therefore leads to the creation of relations between them. Example of studies of proximity view include, for example, knowledge-sharing (Giuliani and Bell, 2005), joint R&D projects (Hagedoorn, 2002), and joint patents (Hoekman, Frenken and Van Oort, 2009). For example, Balland (2012) investigates the evolution of collaboration network and finds that

physical space encourages the formation of research and development collaborative projects within the global navigation satellite system industry. Hansen (2014) shows that organisations that are physically proximate are more likely to form and maintain relations with each other. Physical space increases interactions between organisations reducing costs and risks associated with transfer, social proximity increases interactions in a way that generates opportunities to bring social actors together in order to achieve common goals. In summary, studies on *theory of network* explain the social process behind the formation of relations that is social selection.

As Borgatti & Halgin (2011) pointed out, research on *network theory* describes how the structure of social relations has an impact on a number of organisational behaviours and outcomes. Research on *network theory* uses two perspectives in describing the consequence of inter-organisational networks, such as embeddedness and contagion or diffusion (Borgatti and Foster, 2003). Embeddedness view stems from the insight that individual behaviour is constrained by relations with others (Uzzi, 1997). For example, Soda & Usai (1999) use relational capital to investigate the effects of network embeddedness both for dyads and for the network as whole. They find that relational capital increased in the dyads while decreased within the whole network. The findings suggest that a collaborative network generates a negative effect on the whole economic system, representing a source of instability for the individual firms in the network. The second perspective is social influence or contagious process and it stems from the insight that the behaviour of organisations is affected by other organisations. For example, the abandonment of a strategy is contagious because leaders examine what other organisation are doing to better understand when to change their strategy (Greve, 1995). An important mechanism that has been linked to contagious process is adaptation: the tendency to become progressively similar in behaviours as outcome of adapting to the same environmental forces (Borgatti *et al.*, 2009). It is important to note that social influence not only occurs when organisations are directly connected to each other, but also when organisations are indirectly connected to each other (Mizruchi, 1993) and it could occur as a result of one organisation copying or imitating another.

Considering what has been explained in these subsections, table 2 summarizes the state of empirical research in inter-organisational networks. By doing a keywords search “inter-organisational relations”, “inter-organisational networks”, “networks”, “organisations”, “collaboration”, “competition”, “coopetition”, and “network approach”. There were 61 papers

in the area of business, management and accounting, and social sciences in English and peer-reviewed journals. The top 15[1] cited articles are presented in table 2.

Table 2: Examples of classic studies on inter-organisational networks.

Author	Network Mechanism	Theory	Level of analysis	Research design	Finding
Ahuja, 2000	Antecedents	Resource dependency – based	Ego-networks	Longitudinal	Network formation is positively correlated to opportunities in terms of resources and performance.
Ahuja, 2000a	Antecedents	Social capital	Ego-networks	Longitudinal	Direct ties and indirect ties have a positive effect on organisational performance, while structure holes have a negative effect on performance (innovation).
Powell et al., 1996	Antecedents	Resource-based / knowledge - based theories	Ego-networks	Longitudinal	Partners are chosen based on whether they could complement resources and capabilities of an actor in an alliance, hence dissimilarities may be more attractive than similarities.

[1] The top 15 cited articles are the classic studies in this field and have over 500 citation on average. Several exclusion criteria to restrict topic that were not relevant as being used such as organizational lifecycle, marketing, tourism etc.

Whittington et al., 2009	Antecedents	Resource – based / proximity	Whole networks	Longitudinal	Density and geographical location are good predictors of inter-organisational relations formation among proximate organisations.
Zaheer, McEvily, & Perrone, 1998	Consequences	Trust- based theory	Dyadic-level	Cross-sectional	High inter-organisational trust between organisations is associated with lower transaction costs. They also show how inter-organisational trust between organisations may influence organisational performance.
Sorenson & Stuart, 2008	Antecedents	Resource – based theory/ economic exchange	Dyadic level	Longitudinal	Organisations are more likely to create collaborative relations with dissimilar partners that come from different specialization industries.
Gargiulo &	Consequences	Social capital	Dyadic level	Cross-sectional	A high level of cohesion generates negative effects or

Benassi, 1999					externalities on organisational outcomes.
Gulati, Nohria, & Zaheer, 2000	Consequences	Resource – based theory	Whole network	-	The characteristics of structural networks in which organisations are embedded has a positive impact on organisational performance
Powell et al., 2005	Antecedents	Institutional theory	Whole networks	Longitudinal	Organisations increase their collaborations with diverse partners whereby new resources are channelled and combined.
Baum, Calabrese, & Silverman, 2000	Consequences	Resource-based / Social capital	Dyadic-level	Longitudinal	Structural position of organisations within the whole network is positively correlated with organisational performance.
Gulati & Gargiulo, 1999	Antecedents	Embeddedness	Dyadic - level	Longitudinal	Organisations are more likely to develop inter-organisational relations with similar partners. Furthermore, the network location of

					each organisation encourages the formation of inter-organisational relations.
Greve, 1995	Consequences	Institutional theory	Ego-networks	Longitudinal	The abandonment of a strategy is contagious because leaders examine what other organisation are doing to better understand when to change their strategy.

Following this theoretical distinction, Borgatti & Halgin (2011) pointed out that antecedents and consequences are likely to be linked to each other giving shape to what has been called to "*network theory of networks*". This view is echoed in Brass, Galaskiewicz, Greve, & Tsai (2004:809) where the authors emphasize that 'networks create outcomes that are, in turn, antecedents for network development' hence emphasizing the co-evolutionary perspective of IONs.

2.4 The co-evolutionary perspective in IONs: network theory of networks

In their review of the inter-organisational literature, Brass et al. (2004) provide a different approach on inter-organisational relationships and networks. Taking a holistic approach, they investigate organisational network study at the interpersonal, interunit and inter-organisational levels of analysis. The focus on the antecedents and the consequences of networks at each of these levels, underlining the importance of joint investigating these levels in order to investigate organisational network phenomena. In a similar vein, Borgatti & Halgin (2011) define network theory of networks as situation where independent and dependent variables include network properties. Studies that have used this perspective emphasise the importance of dynamic as change that affect the structure of the network in which organisations are embedded (Light *et al.*, 2013). Only recently organisational scholars have recognized the benefit of adopting the co-evolutionary perspective, for example Amati et al. (2019) show how

change in the portfolio of activities that organisations held involve change in the composition of portfolio of network partners. They find two sets of mechanisms that work across two different levels to influence the co-evolution of organisational and network structure. Stadtfeld et al. (2016) show how multiple networks co-evolve with other over time by identifying two mechanisms, i.e. assimilation and differentiation that shape organisational and network structure. They find that similarity and differences among connected organisations are results of the social influence processes. Gygax, Hazledine, & Martin (2017) using a sample of S&P 500 organisations in the USA, show how network structure and financial behaviour of organisations co-evolve. Benton (2017) investigates how organisations assimilate corporate governance behaviour and he finds how cohesive groups are created through actor-driven mechanisms, i.e. directors are affiliated with similarly dense group of organisations and interlocks foster organisations to adopt practices of their network neighbourhood.

Therefore, studies in this perspective are limited and this calls for further developed aim at understanding on how organisational behaviours and network structures mutually influence each other and co-evolve (Tasselli, Kilduff and Menges, 2015).

2.5 Research on IONs and Health

A social network approach has been used extensively also in the healthcare management and health economics literature. Taking the relational lens to investigate healthcare system, hospitals are embedded within a network of interactions rather than isolated actors. Coordination among hospitals is becoming increasingly important because it enhances the level of efficiency and quality in the system (Provan and Milward, 2001). Indeed, integration among hospitals is considered one feature of the healthcare system (Gittell and Weiss, 2004). Some researchers have argued that lack of coordination among healthcare providers generates negative consequences at system level with the increase of costs of service utilization and generates a higher rate of patient mortality and readmissions (Lu and Lu, 2018). As Provan & Milward (2001:416) pointed out “efficient services delivered by multiple agencies may not be as appealing to some stakeholder groups when the coordinating activities of these agencies are not well understood”. Therefore, the development of inter-organisational relations play an important role in the healthcare system. Firstly, they enable hospital organisations to access information held by other organisations within the system. Secondly, they encourage mutual awareness, knowledge sharing and trust (Chen, Preston and Xia, 2013). Finally, they affect

technological integration, which, in turn, impacts clinical and hospital performance (Mahoney *et al.*, 2007).

By using inter-organisational collaborative relations as a framework to investigate interconnections among different actors within the healthcare system. Hospitals tend to create relations with other social actors through which information, assets and status are channelled. These relations come in different forms created for a specific purpose and can be studied both at horizontal - i.e. between healthcare providers that work in a similar domain - and vertical dimensions - i.e. between healthcare providers that work in different domains- (Westra *et al.*, 2017b). There are different forms of inter-organisational collaborations, for example strategic alliance that are voluntary arrangement which aims at exchanging co-development of products technologies and services (Gulati, 1999). Partnership aims to include non-public partners (Ferlie and McGivern, 2003). Consortia and joint ventures aim at facilitating the access to market and resources (Fottler *et al.*, 1982; Barringer and Harrison, 2000). Interlocking directors aim at facilitating communications and coordination between hospitals that in turn, affects organisation's financial sustainability and improve health outcome i.e. accessibility of care (Westra *et al.*, 2017a).

The establishment of these forms of inter-organisational collaboration follow different criteria. Mascia, Pallotti, & Iacopino (2018) suggest three criteria: the first criterion is the distinction between relations created on a voluntarily basis; the second criterion is the distinction between relations based on the degree of formalization; and the third criteria criterion is the distinction between relations based on the degree of differentiation. More specifically, voluntary basis refers to relations that are created aiming at achieving specific strategic goals, while involuntary basis refers to relations that are imposed from the external environment, i.e. normative change and coercive pressure. Degree of formalizations refers to i) relations that are established as the outcome of top-down decisions; and ii) informal relations that are established among and between individuals that, in turn, have an impact on organisational behaviour. Differentiation refers to the decision-making level where collaboration occurs, organisational versus individual level.

However, inter-organisational collaboration relations can also involve the creation of informal social relationships rather than contractual arrangements among healthcare providers (Mascia, Pallotti and Iacopino, 2018). Coordination is partially planned and stems when healthcare providers establish collaborative relations that aim at achieving collective purpose. Trust,

mutual awareness, personal relations, shared knowledge and information are the key-factors that drive the formation of informal social collaborative relations among healthcare providers (de Figueiredo and Silverman, 2017). Patient transfers is considered one form of inter-organisational collaboration (Lomi and Pallotti, 2012). Although transferring patients from sender to receiver healthcare providers is recorded officially, it may well require informal relationships among healthcare providers to prepare it. Therefore, patient transfer encourages the formation of relations through which knowledge is channelled (Westra *et al.*, 2017b). This type of inter-organisational relations also stem from deliberate decision to involve partner in the delivery of care services and respond to fragmentation nature of healthcare and increasing specialization of healthcare providers (Antivachis and Angelis, 2015). As Gittell & Weiss, (2004:59) suggest 'to discharge patients properly requires some kind of relationships with downstream providers who will care for the patients post-discharge, both to assure that slots will be available on short notice, and to assure that once gone, patients will be in good hands'.

Patient transfer has been studied among physicians and it has been called "inter-professional networks"; it has also been studied among hospitals and it has been called "inter-hospital patient networks". Inter-professional networks occurs when physicians collaborate with each other via patient transfers within/ outside wards (Hilligoss and Cohen, 2013). Inter-hospital patient network occurs when hospitals collaborate with each other via patients sharing. Collaboration is unplanned, and it is an outcome of joint problem-solving arrangements, enabling hospitals to coordinate their activities for the solution of common clinical problems. While studies that investigate other forms of collaboration, such as inter-professional networks have a long tradition in this field, studies that focus on inter-hospital patient relations have only been investigated over the past few decades (Lu & Lu, 2018; Lomi et al., 2014;Veinot, Bosk, Unnikrishnan, & Iwashyna, 2012; Iwashyna & Courey, 2011). Different factors drive inter-hospital patient transfers relations, such as the lack of resources for clinical treatments at the sender hospitals – this is particularly the case of emergency settings (Veinot *et al.*, 2012), but also clinical information and knowledge, for both the sender and receiver hospital (Kitts *et al.*, 2017). Moreover, physical distance, quality measures, personal relationships, and capabilities complementarities are also factors that determine the creation and endurance of inter-hospital patient relations. For example, Mascia & Di Vincenzo (2011) find that collaboration via patient transfer relations occurs between and among hospitals that are located in similar geographical areas – where hospitals are in competition for the same resources i.e. patients.

Despite a plethora of research in inter-organisational collaboration in healthcare field, scholars argue that there is a need to explain the evolution of this network in healthcare domain (Mascia, Pallotti and Iacopino, 2018; Westra *et al.*, 2017b). This calls for further investigation of inter-organisational collaboration relation via patient transfers influences on the overall performance of the healthcare system and thus in turn improves the level of efficiency within the system.

2.6 Conclusion: Gaps in the literature and areas for contribution

The main goal of this literature review was to provide an overview of studies in inter-organisational networks. In the past few decades social networks analysis has used as relational lens to investigate organisation and inter-organisational relations (see R. S. Burt et al., 2013; Borgatti & Halgin, 2011; Kilduff & Brass, 2010; Borgatti et al., 2009). The literature is large and dense, involving different levels of analysis (Zaheer et al., 2010; Provan et al., 2007; Brass et al., 2004; Borgatti & Foster, 2003).

Traditionally, studies on inter-organisational networks relied on cross-sectional design which investigates static network with organisations linked by stable relations (Lin *et al.*, 2017). The growing recognition that relations influence organisational behaviour also requires a theory explaining how and why inter-organisational networks evolve in the first place, so that longitudinal investigation is needed (Valente & Pitts, 2017; Rivera et al., 2010). Different factors enable the transition from statistic to dynamic investigation in inter-organisational networks, such as methodological advances in modelling relational data, availability of data, these provide an insight in how inter-organisational networks evolve. These developments contribute to create a conceptual clarity on how connections among organisations shape organisational behaviour over time. These new dynamic approaches open opportunities for organisational scholars to unfold the concept of similarity in inter-organisational networks.

This dissertation contributes to the investigation of inter-organisational networks in different ways. First, this dissertation explores the concept of similarity and its different dimensions in studying organisation behaviour at inter-organisational level over time. Chapter 4 zooms on the consequences of inter-organisational networks by using the concept of peer effects defined as the association among organisational outcomes. This leads to the investigation of similarity as output. Chapter 5 looks at the antecedents of inter-organisational networks by using the concept of social similarity as moderator between geographical distance and inter-organisational resource transfers. This leads to the investigation of similarity as social space. Chapter 6 looks at the effect of complementary partners on the dynamics of collaborative

relations among organisations by using the different dimensions of complementarity. This leads to the investigation of similarity as multiform dynamic. Second, this dissertation applies econometrics model and stochastic actor- oriented based model in order to take the temporal dimension of selection and influence processes that unfold over time. Finally, this dissertation contributes to the literature on healthcare by using data on patient transfer relations.

Keeping in mind the gaps and areas of contribution, Table 3 shows how each empirical essay addresses these gaps and how the concept of similarity and inter-organisational networks are integrated.

Table 3: Identification of the gaps and corresponding empirical paper

Inter-organisational theory	Level of analysis	Addressing gap	Contribution
Network of theory	Dyad	Growing evidence of peer effects on organisational outcomes in economics field (Falk and Ichino, 2006) however few studies have investigated peer effects operate at different network levels on organisational outcomes	Using inter-organisational literature and economics literature, the first paper makes a bridge between these fields by understanding how peer effects operate at three different levels: dyadic, network subgroups and network positions.
Theory of Network	Dyad	Growing evidence that geographical proximity and social similarity encourage the formation of network ties. However, the concept social similarity is measured	The second paper introduces a new measure of social similarity relying on a positional rather than a relational concept and uses social similarity as moderator

		in many different ways shows large amounts of overlap with the other dimensions of proximity, i.e. organisational proximity. The topic is agued to constitute one of the main gaps in the literature, as is shown in Knoben & Oerlemans (2006)	
Network theory of networks	One-mode network	Growing evidence of complementarity and geographical location affects partner selection decision (Soda and Furlotti, 2017; Furlotti and Soda, 2018), however identification of the joint effect of complementarity and geographical location affects mechanism networks to change in organisational performance is needed.	The third paper clarifies how different dimensions of complementarity interact together and affects collaborative network dynamics.

Chapter 3: Empirical setting and data

The empirical setting of this dissertation is healthcare sector in Italy. More specifically, this dissertation uses a longitudinal data collected on collaborative relations observed during a four-year period (2006-2009) among hospitals providing healthcare services in Lazio- a regional community located in Central Italy. Collaborative relations is captured through patient transfers.

This chapter describes the empirical setting and the data that inform my research. However, a detailed description of the data and samples are contained in each of the chapters that are structured as independent and self-contained studies (Chapter 4-5-6). The rest of this chapter is structured as follows. The first section describes the Italian National Health Care System (called Servizio Sanitario Nazionale, SSN). The second section discusses the Lazio healthcare system. The third section describes patient transfer relations as a form of inter-hospital collaboration. Finally, the fourth section describes the data.

3.1 Italian National Healthcare System: from national to 21 regional health services

Italy established its healthcare system in 1978 aimed at providing universal, uniform services and replacing the previous system of health based on private insurance (Anessi Pessina & Cantu, 2004). The SSN is funded by a tax-based system (Abadie *et al.*, 2011). It provides universal free-of-charge coverage, at the point-of-service to all population - and since 2002- includes foreigners with legal residence (Ferré *et al.*, 2014). The reform introduced three different levels: the first is the national level; the second one includes the 21 independently autonomous Regional Health Services (RHSs); and the final one includes 139 semi-independently autonomous Local Health Units (LHUs) (Tarricone and Borgonovi, 2015). The national level is responsible for setting the financing and distributing funds to the regions as well distributing tax financing through the National Health Fund, and for setting the National Health Plan (called Piano Sanitario Nazionale, PSN). RHSs are responsible for local planning according to the goals specified by the central government and for organizing and managing healthcare services and allocating resources to the local level. Regions become the third payers or purchasers (with respect to public funding) together with private insurance companies (with respect to non-public funding) in the Italian system of healthcare (Scalzo *et al.*, 2009). Finally,

the local level is responsible for setting the funding within the regions. Initially, this reform had positive consequences on the regional health expenditure: in 1977 health expenditure decreased by 28% in the South and 36 % in the Centre-north compared to the national average (Fargion, 2006,1992,).

Following the model of the British National Health Service, the idea of centralized system of financing was expected to help the government to better control the health spending (Frisina Doetter and Götze, 2011). Nonetheless, the INHS was not so effective like the Britain model due the fact that central government was unable to control and monitor the overspending from the regions. When regions go beyond the budget, the central government covered the deficit thereby increasing the negative incentives for both regions and providers to overtake their budgets (Ferré *et al.*, 2014; Frisina Doetter and Götze, 2011). Therefore, budget deficit was the crucial problem of the INHS (France, 2005). This led to the second round of reforms during the early 1990s aimed at containing healthcare costs and improving the level of efficiency through the allocation of finance responsibility at local and intermediary level. According to this, the relationship between RHSs and LHUs can be seen as that of "parent and subsidiary" where the RHSs represent the parent company and LHUs its subsidiaries (Anessi Pessina & Cantu, 2004).

More specifically, the second round of reforms was initiated in 1992 and concluded with the process of fiscal federation in 2009. The 1992/3 law introduced three different but interconnected points: managerialism, regionalization or decentralization and quasi- market in the Italian Healthcare system (Anessi Pessina & Cantu, 2004). Managerialism has been introduced at local and intermediate levels, whereby the RHS pushed their LHUs to improve their level of performance and to adopt private sector management techniques (Ferré *et al.*, 2014). The process of regionalization gave the opportunity to regions to organize their healthcare services locally by introducing different governance models with respect to three points: i) foster the level of competition into their regional healthcare services; ii) introduction of a purchaser-provider split; iii) move from traditional top-down decision making to the reorganisation of the local health authority into public entities that are managed by a general managers. Within this framework, regions had the possibility to adopt different governance models, and this brought significant interregional differences (Ferré *et al.*, 2014; Frisina Doetter and Götze, 2011). For instance, Lombardy was the only region to adopt the purchaser-provider split template, while two governance models have been embraced by the remaining regions. Centre-north and north-east embraced the LHU-centred template based on the

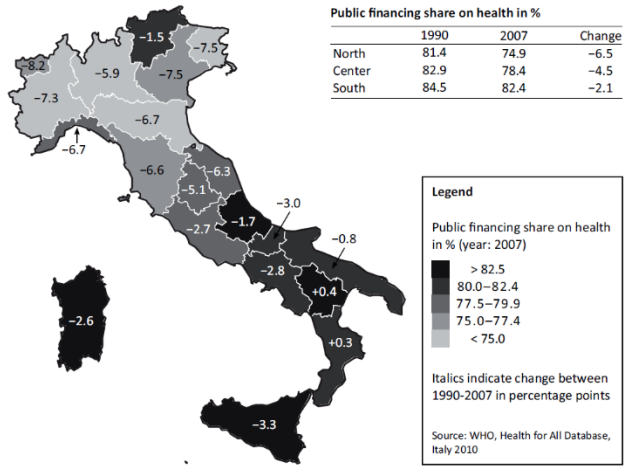
governance model of cooperation and integration. Under this model, the regional healthcare system is seen as network where each public and private provider is seen as complementary actor rather than competitor. South embraced the residual – incrementalism model based on the idea of integration and cooperation as governance tools, however the regulatory scheme was unclear (Neri, 2009, 2006).

The process of regionalization has been supported with the introduction of quasi-market that fostered competition at regional and local levels through free patient choice and the introduction of a new reimbursing scheme called "Diagnosis Related Groups" (DRGs), as prospective payment for hospital activity (Sanita' di & Better, 2018). The quasi-market is based on the idea that money follows patients whereby each region decides the total amount to be spent on healthcare services and put them at the disposal of LHUs on a capitation basis (Ferré *et al.*, 2014). This financing scheme given from the regions to LHUs cover all services provided by the LHUs itself and other providers, i.e. private accredited providers. On the other hand, LHUs reimburse other providers for care given to their residents as patients can choose any providers within and outside their LHUs of residence. Reimbursements are DRG-based for hospital discharges and free-for service for out-patient services (Ferré et al., 2014; Anessi Pessina & Cantu, 2004). The Diagnosis Related Groups system aimed to classify hospital services into groups in terms of similar diagnosis and classify patients according to their pathologies (Bellavia *et al.*, 2012). Each category has been associated to a fixed price for which hospitals (both private and public) are reimbursed. According to this framework, each LHUs is expected to provide a complete range of services to its residents, otherwise they would be penalized if their residents look for care from other providers.

The rationale behind the reform was to give more freedom to the regions in designing their own funding system, in delivering healthcare services, and in controlling the regional healthcare expenditure. Such reasons were emphasized with the constitutional amendment in 2001, which encourage the regions to provide all services to their population in line with the list of services set by the central government (France, 2009). During this period, the political climate and the financial obligations to the European Union led to reconsideration of the role of central government on controlling regional performance in healthcare. This was stressed through two important acts called "State and Regional Accords" in 2001 and the "Pact for Health" in 2005. The pacts also specified the role for the central government to provide financial support to the regions. However, the process of decentralization is still seen as a feature of the INHS. This has been underlined by the recent reform on fiscal federalism in 2009

that aims at increasing more financial autonomy to the regions, i.e., regions decide how to spend their budgets align with the guidelines of the central government. For instance, currently regions spend 70% of their budgets to health services and control 90% of public expenditure on healthcare (Tarricone and Borgonovi, 2015). On the one hand, after twenty years, regionalization is still considered as the policy solution to the healthcare spending. On the other hand, the role of the central government in healthcare spending differs across regions[2] with an increasing gap between north-south Italy: in 1990 the gap was 3.1% points while in 2007 accounted for 8.5 % points (Frisina Doetter and Götze, 2011). This also reflects the role of the central government in supporting the regions, where southern regions have higher level of public financing shares compared to other regions in 2007 as shown in figure 3.

Figure 3: Public financing share across the regions: 1990-2007– source: Frisina Doetter & Götze, 2011

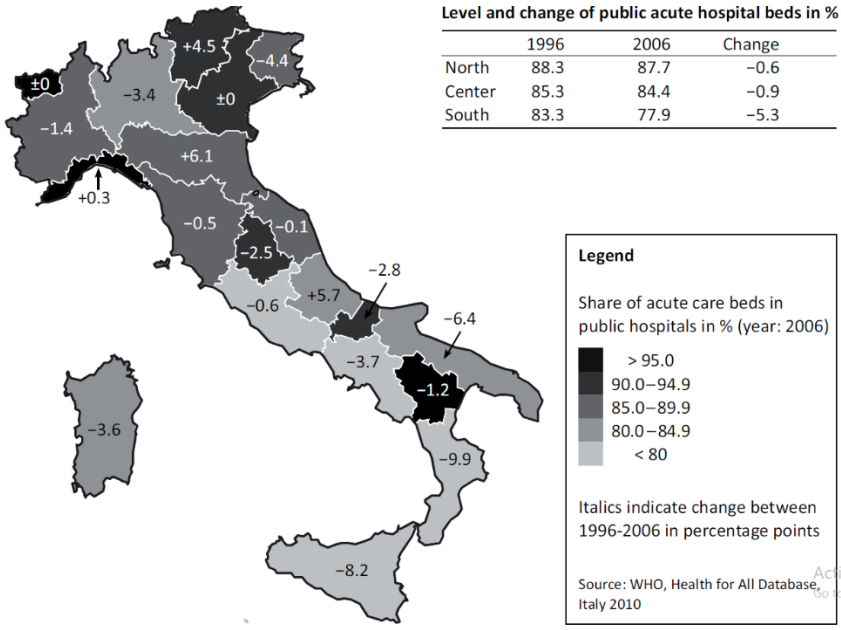


The role of the central government combined with the process of decentralization could also be observed in the delivery of healthcare services, especially in the inpatient care sector. Over time, the role of financial funds to inpatient care did not change whereas in 1988 inpatient care accounted for 47.1 % and in 2009 was 47.9% (Frisina Doetter & Götze, 2011). In this sector, hospitals play an important role where the healthcare services are delivered by private and public hospitals. The number of hospital beds in public hospitals decreased from 1978 to 2006, where the public share was for 78.7 % in 2006 (7.3 points less than at the introduction of the SSN in 1978) and with 3.9 beds per 1000 inhabitants – as shown in Figure 4 (Frisina Doetter and Götze, 2011). The share of public beds also captures the gap between the North and South of Italy, where many private clinics are paid by public funds in Southern regions (Tarricone &

[2] It should be noted that regions differ in terms of the size of population and economic conditions

Borgonovi, 2015; Bocconi & sulle Aziende, 2013). Therefore, the southern market is characterized by the presence of private providers as the regions' administration fail to control healthcare spending and to provide equity in the delivery of health services (Neri, 2009; France & Taroni, 2005).

Figure 4: Public hospital beds in the Italian regions – source: Frisina Doetter & Götze, 2011



In Lombardy, however, the share of public beds is reduced over time given the fact that the region adopted the purchaser-provider split in which a higher number of private hospitals have been accredited.

The 1992/3 reforms also led to the introduction of hub and spoke configuration that involves the creation of main campus or hub which receives higher amount of resource investments and deliveries the most intensive medical services, integrated by spokes which offer limited services at different local points located across the served market (Ferré *et al.*, 2014). The hub and spoke configuration aim at improving the level of coordination among hospitals whereby the monitor of healthcare spending is essential to improve the level of efficiency in the system. Summing up, since its creation in 1978, the Italian National Health System has been characterized by important modification: from the regionalization to the introduction of quasi – market principle. The main reasons of these changes in regulation were to give liberty of identifying how and in what manner regions could direct answers to the problem of healthcare spending, and on other hand, to create a homogenous internal market. Contrary to the English

model, where the internal market has been uniformly created, in Italy these new forms of regulation have introduced an important interregional difference and failed the INHS in monitoring regional spending. Indeed, the problem of regional spending still remains the main issue of the INHS. Nevertheless, the highly regionalized of National Health service could be seen as the main reform came from the regulation process.

3.2 Organisational structure: three different levels

At national level, the central government through the Ministry of Health has the following responsibilities:

- The role of stewardship, including the allocation of national funds to the regions;
- To set the fundamental objectives and goals of the healthcare system, including the definition of "essential levels of care" (called livelli essenziali di assistenza sanitaria, LEA);
- To dispose of the core health services available to the citizens across the country;
- To monitor the SSN;
- general governance of the National Institute for Scientific Research (called Istituti di ricovero e cura a carattere scientifico, IRCCS).

The Ministry carries out the above-mentioned responsibilities through three different independent and specialized departments such as i) department of public health and innovation, ii) department of planning and organisation of SSN; and finally iii) department of veterinary care, food safety and collegial organs for health protection. It is also supported by different government agencies, for example the national institute of health (ISS) that promotes public health and carries out scientific research; the national agency for regional health services (AGENAS) that acts between the Ministry of Health and regional authorities that monitor the quality, the efficiency and efficacy in production of services care. Beyond this national framework, the largest issues that SSN has to face are: to maintain cost and achieve budgetary goals without reducing patients' access to healthcare; to ensure equity across regions; to promote coordination or collaboration between different actors within the health community; and to support innovation among healthcare providers across regions.

At regional level, regional authorities have the following responsibilities:

- To distribute financial resources among healthcare providers;
- To set technical and management guidelines for service provision and planning;

- To decide general principles and organisation of the regional healthcare system, including general rules about regional authorities and agreement with private providers.

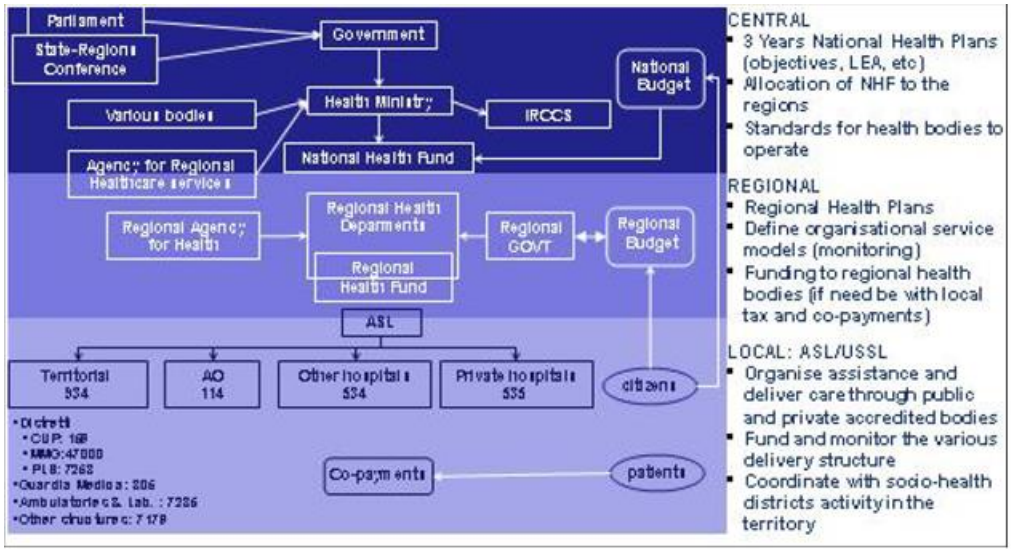
Regional authorities carry out the above-mentioned responsibilities through the regional Department of Health. Each Region has its own regional health responsible for helping the regional health department itself and to provide technical support to the local authorities such as LHUs.

Finally, at local level the local health units are responsible for delivering healthcare services through their own facilities (public hospitals) and private hospitals to their population. LHUs are under control of their own regional authorities, which fund them according to financing scheme. Each LHU has to coverage their population (Ferré *et al.*, 2014). LHUs have the following responsibilities:

- To set preventive medicine and public health services;
- To guarantee the delivery of basic treatment through a network of general practitioners that provide family medicine services;
- To guarantee community services including primary medical and nursery care;
- To ensure secondary care through their public hospitals according to their budget;
- To accredit private hospitals and specialists;
- To deliver social care and social welfare services.

Figure 5 summarizes organisational structure of the Italian NHS.

Figure 5: Organisational structure of the INHS – source: Zincone & Basili, 2010



3.3 Lazio healthcare system from 2006 to 2009

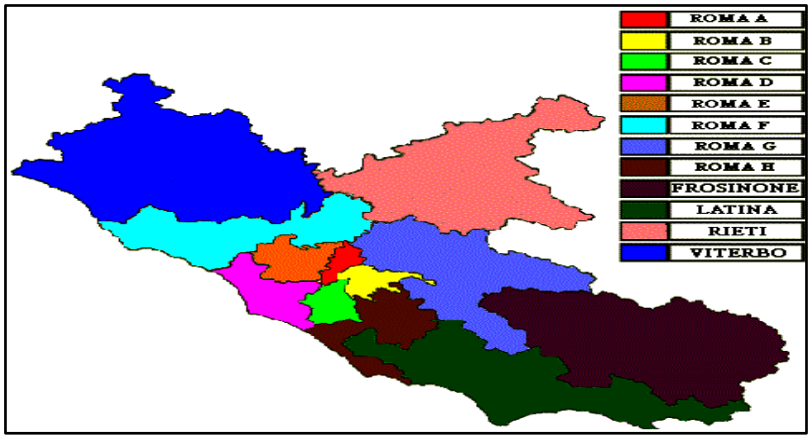
Lazio had adopted the quasi-market institutional framework aimed at promoting the equity benefits of traditional system of public healthcare management and financing, while enhancing the potential efficiency derived by market competition (Barretta, 2008). As discussed above, this institutional framework is the result of the ongoing regulations that started in the 1990s with the goal of improving the performance of single hospitals and the whole system. Under this framework, Lazio has the choice of how much resources to spend in the healthcare sector although it has to reach a financial equilibrium to align with the relative assessment criteria. Over the last years, indeed, the region plays major role on healthcare spending (Bocconi and sulle Aziende, 2013). Table 4 reports the regional annual balance for healthcare sector.

Table 4: Regional balance for healthcare expenditure. Source:ASP Lazio

Regional balance				
	2006	**2007**	**2008**	**2009**
In – pocket	10.721	11.610	11.991	12.367
Out-pocket	10.709	10.972	11.991	11.534
Balance	12	638	726	834

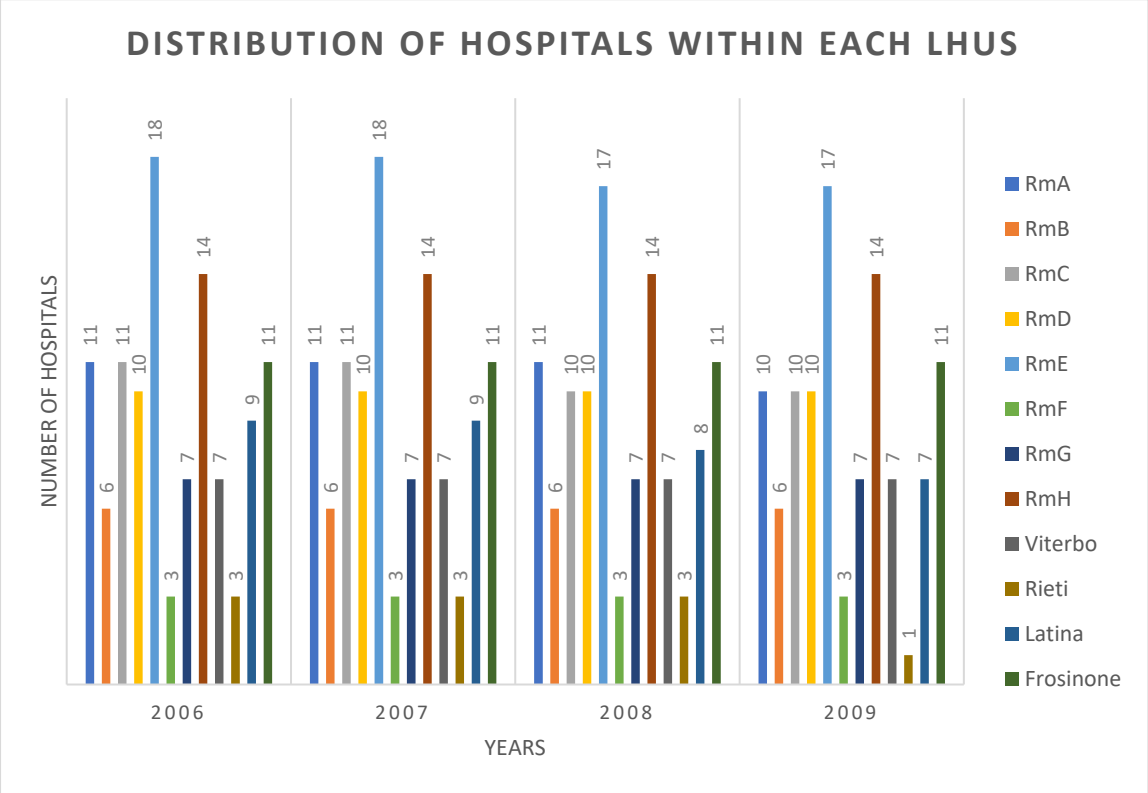
Since the patients are free to choose their healthcare providers and the reimbursed system for services is diagnosis- related grouping based, the region is strongly motived to invest in quality in order to attract patients, control healthcare spending, and generate a stable cash flow. Lazio provides healthcare services through the Local Health Units. LHUs ensure the delivery of their health services to patient population, coordinating the services provided by 12 LHUs, 8 of which are localized in Rome – the capital city- and 4 covering the area of the other provinces of the Region, that are Viterbo, Rieti, Latina and Frosinone. Figure 6 shows the partition of LHUs in Lazio.

Figure 6: Map of Lazio with the 12 Local Health Units



The higher concentration of major hospitals supplies healthcare services across the market of Rome, where the LHUs of RmF has 70 hospitals over time and a more dispersed distribution of smaller hospitals in the periphery. Figure 7 shows the total number of hospitals within each LHUs from 2006 to 2009.

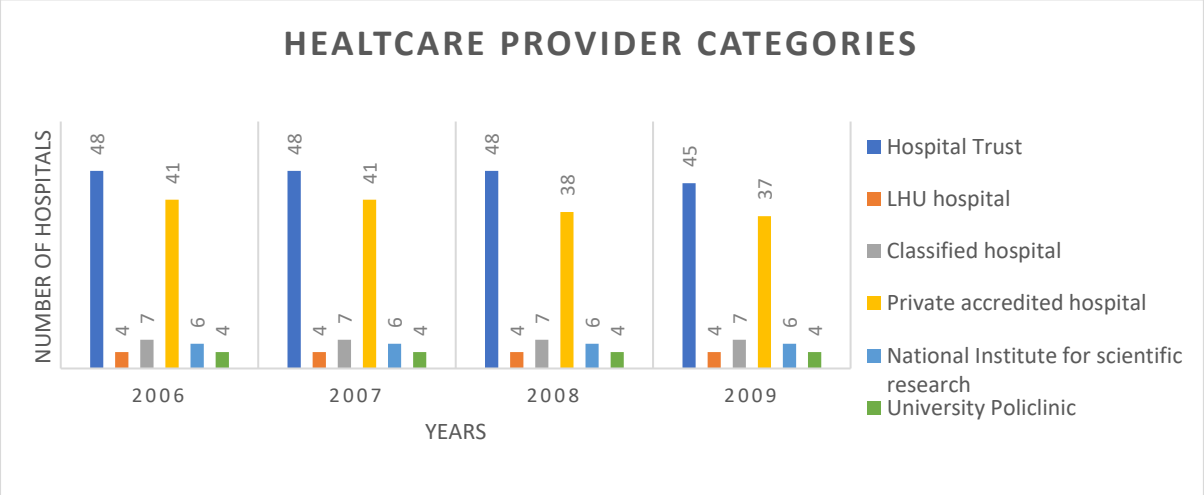
Figure 7: Distribution of hospitals within each LHUs



The existence of different ownership typologies of providers, which has been encouraged by the publicly funded quasi-market framework, can be grouped into six main categories. The first

category comprises public hospitals, including LHU hospital; Hospital Trust and University Policlinics whose activity is partly committed to teaching. The second one comprises private hospitals, including accredited and classified hospitals, which offer their services to the regional system. Finally, the mixed- nature category, includes the National Institutes for scientific research both publicly and privately, owned whose activity is partly committed to research (Gianino *et al.*, 2006). The figure 8 shows the different providers based on their type of ownership-governance structure that are present in Lazio during the year-period 2006-2009.

Figure 8: Healthcare providers in Lazio 2006-2009



During the period 2006-2009 some hospitals closed, showing variation in the number of hospitals operate in the region. In 2006 and 2007 there were 110 hospitals, in 2008 there were 107 in 2009 were 103. As discussed above, the majority of hospitals are located in Rome: 50% of hospitals belong to LHUs of Rome where more than of 60% of population lives in the capital city of Rome.

Regarding hospitals' bed capacities, hospitals have 4.2 beds per 1000 inhabitants while public beds is 3.5 per 1000 inhabitants; there are 17.582 number of beds of which 10.804 is in the capital city (Rapporto, SDO, 2010). The ability of hospital management to allocate their internal capacity both effectively – in terms of quality of care offered – and efficiently – in terms of costs – is measured by the percentage of ordinary hospital beds occupied at given time, such as the occupancy rate. As a consequence of national policies and the reallocation of beds, public hospitals show a higher percentage of occupancy rate than the private ones (Rapporto SDO, 2009). Regarding the attractiveness of the area in terms of patient flows, Figure 9 shows the share of hospital admissions made in the LHUs of the patient's area of

residence. It should be noted that patients that belong to the LHUs of Latina and Frosinone tend to make greater use of the hospitals operating in their area of residence i.e. LHU hospital, classified hospital and private accredited hospital (Rapporto SDO, 2009).

Figure 9: % of hospitalizations of residents made in the same LHU of residence – Lazio 2005- 2009 – source ASP, SIO

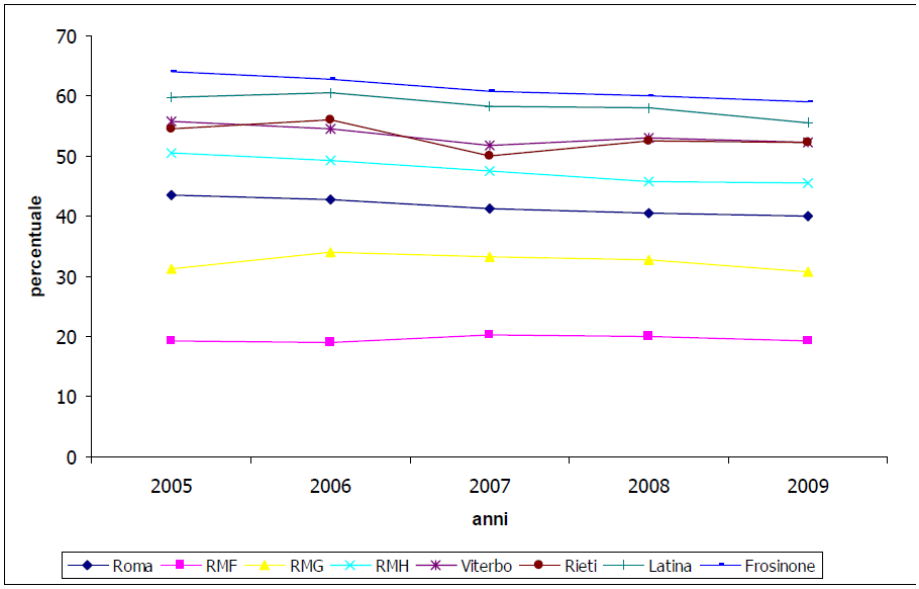
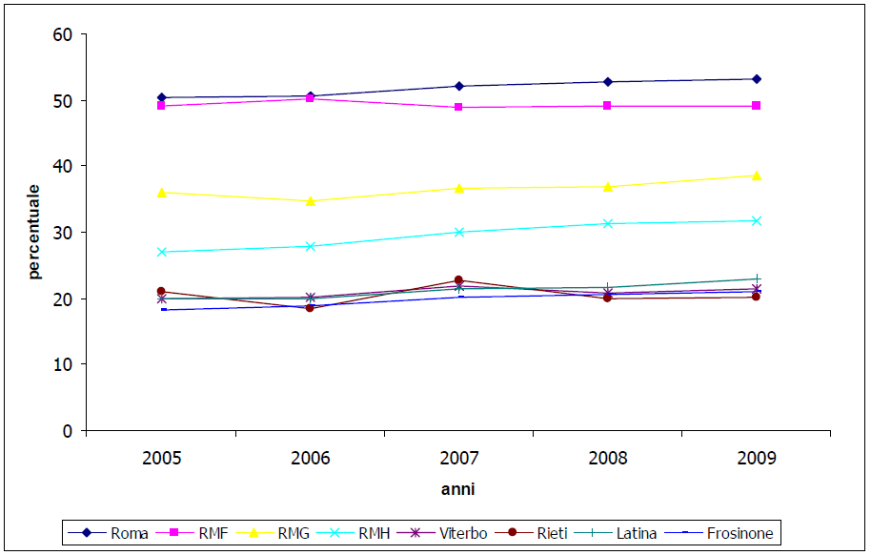


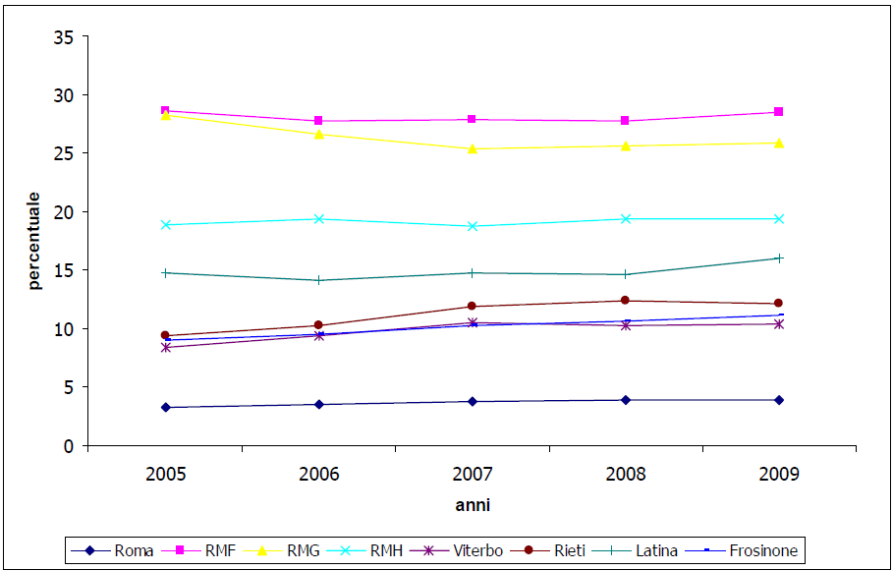
Figure 10 shows % of hospitalizations of residents carried out by hospital trust, university policlinic and national institute for scientific research where the number of hospital admissions increased from 50.4 in 2005 to 53.2% in 2009 (Rapporto, SDO, 2009).

Figure 10: % of hospitalizations of residents carried out through Hospital Trust, University Policlinic and National Institute for Scientific Research Public, Lazio, 2005-2009. Source: ASP, SIO



Finally, patients' mobility is higher for the LHU located in the periphery of the capital city and for the LHU of Latina that accounts for more of 15% in 2009 (Rapporto SDO 2009) as shown in figure 11.

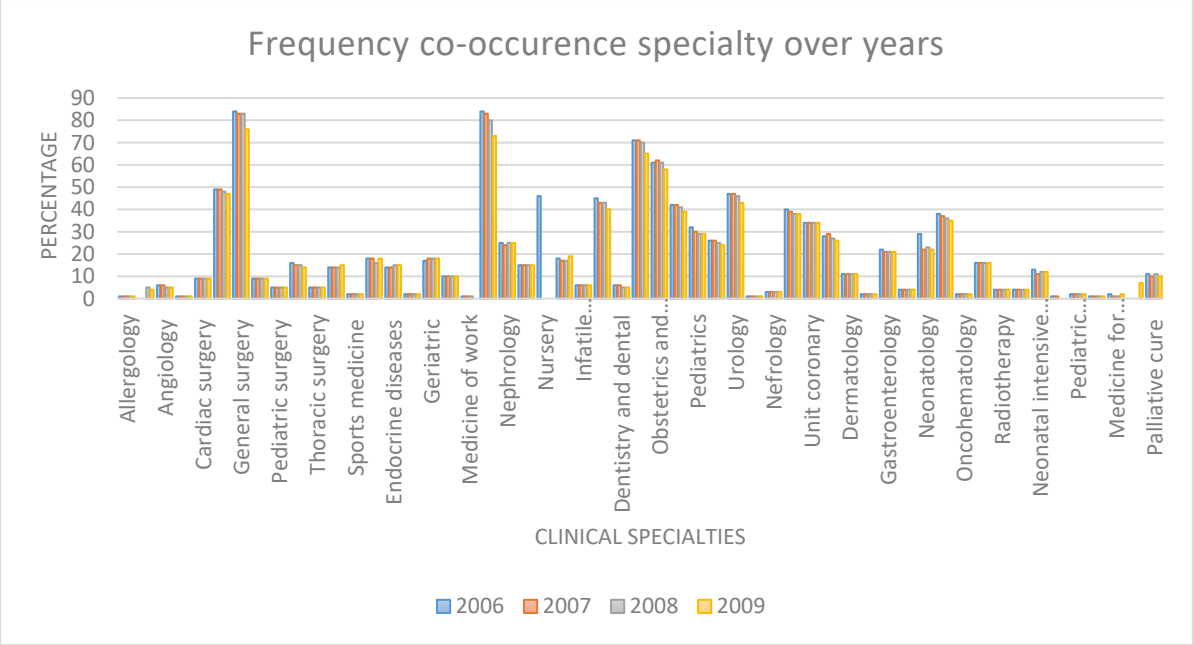
Figure 11: % of hospital admission from other LHU. Lazio, 2005-2009. Source: ASP, SIO



It should be noted that there is an extra-regional patients mobility that is rather limited for the LHU of Rome that is 4%, while it is high for the residents of Viterbo and Rieti that is 20%; it reaches 10% for the LHU of Frosinone; and it reaches 7% for the LHU of Latina (Rapporto SDO, 2009).

Patients mobility is also influenced by the organisational strategy adopted by the hospitals and the clinical services offered. Hospitals, for example, can decide the clinical domain of specialization and the type of services provided to patients. Figure 12 shows the frequency of specialties tend to co-occur over the period examined by this research.

Figure 12: Frequency of clinical services offered by the hospitals over the years



The ongoing process of reforms and intervention at system level has led to introduction of new strategy in terms of organisational model for providers. Hospitals have started to replace the traditional generalist model with the factory model which consists of a narrow set of clinical capabilities in order to deliver more specialized services to patients. Indeed, during these years 20 hospitals decided to adopt the factory model (Rapporto SDO, 2019). The change in their organisational model is decided not only by hospitals managers but also from the healthcare agencies that are in the position to approve or disapprove their strategies. The quasi-mixed framework embodies hospitals to respond to both enhanced quality of services and controlled healthcare balance. As such, the market of Lazio is based on the idea that each health actor does not operate in isolation but is embedded in a network system for the provision of healthcare services. Indeed, in 2010 the central authorities approved a new reform with the goals to promote collaboration between hospitals in order to maintain the costs and to enhance the quality of healthcare services. Collaboration and competition are the key features of Lazio market, in which the delivery of healthcare services is created in order to meet financial equilibrium and control healthcare spending.

3.4 Patient transfer as a form of inter-hospital collaboration

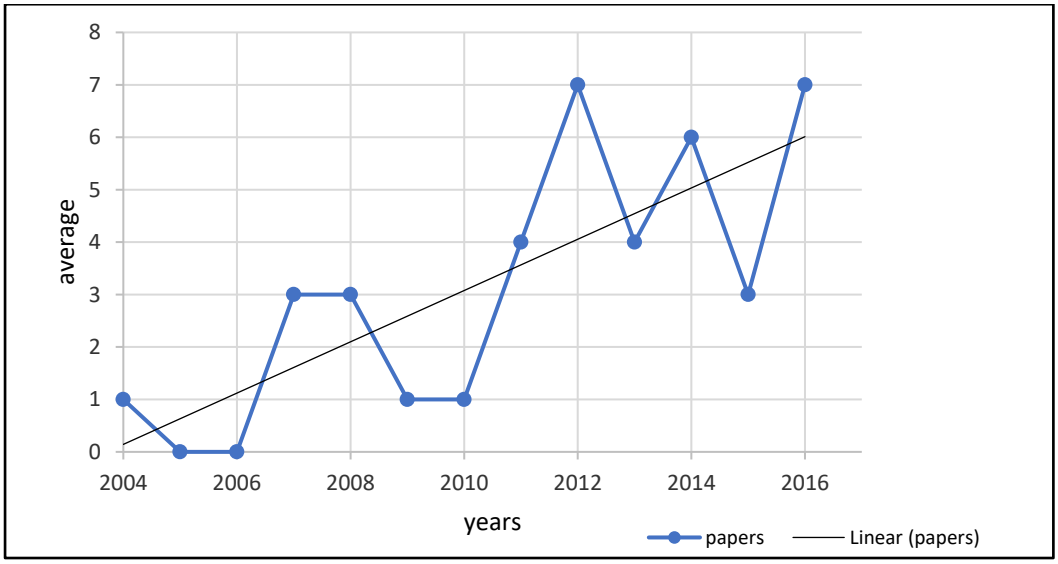
In the healthcare sector, patients are fundamental resources through which hospitals compete and collaborate (Mascia and Di Vincenzo, 2011). Hospitals compete for patients and this leads to competitive patterns in which hospitals recognize their mutual dependency as a function of

their position in a geographical market (Mascia, Pallotti and Angeli, 2017). The fact that organisations share the same basin of resources is positively related to the organisational behaviour, which makes more collaborative arrangements possible (Trapido, 2007). Collaborative ties allow hospitals to allocate resources more effectively; to access knowledge from other healthcare providers'; to share clinical information among them; to achieve common goals; and to improve their performance (Pallotti, Tubaro, & Lomi, 2015; Iwashyna, 2012; Dash & Meredith, 2010). All these activities promote participation, inform decision-making about potential benefits to patients (Iwashyna and Courey, 2011). This implies involving partners in joint problem-solving activities. One way in which hospitals collaborate is through patient transfers. Patient transfer is considered one of the most common forms of inter-hospital collaboration (Lomi & Pallotti, 2012; Lee et al., 2011). It refers to the sequence of paths whereby patients are transferred from hospital "*i* "(sender) to hospital "*j*" (receiver). When the number of patients sent differs from the number of patients received (Iwashyna *et al.*, 2009), the transfer is called asymmetric. According to the literature, it is possible to distinguish another form of inter-hospital transfer of patients called patient sharing which can also be seen as sign of interorganisational collaboration between sending and receiving hospitals (Pallotti, Lomi and Mascia, 2013). Patient sharing involves reciprocal relationships between two hospitals in search of a common purpose (Lee et al., 2011). Despite the directionality of transfer, inter-hospital patient transfers occur when hospitals, that are unable to treat patients with complex pathologies, decide to send patients toward better specialized hospitals in order to improve the quality of care and find the best treatment for them (Lomi *et al.*, 2014). This encourages hospitals to think carefully in order to choose the best possible destination for their patients. It also makes visible the pattern of selection between the sender hospital and the receiver one in which patients' needs are met. (Iwashyna and Courey, 2011). Inter-hospital collaboration requires the use of technical resources like technology (Veinot *et al.*, 2012) and at the same time coordination and clinical information sharing between partners (Gittell and Douglass, 2012). This inherent characteristic of inter-hospital collaboration gives rise to the infrastructure of patient transfers with lower risk for patients' health.

The interest in studying patient transfer as a form of inter-hospital collaboration has been growing in recent years. This can be seen in the exponential growth of number of papers discussing the topic as shown in figure 13. The keyword search are: "inter-organisational networks or inter-organisational networks" and "patient transfers" or "patient sharing"; and "inter-hospital collaboration"; and "social network analysis"; and "organisational

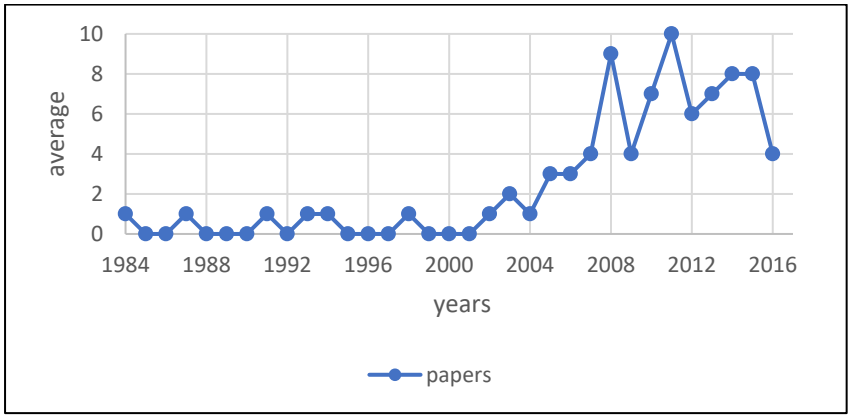
performance" and "organisational networks" on SCOPUS returns 40 papers in total for the period 2004 to 2016 with an average of 3 publications per year . There are 11 papers that consider patient transfer as a form of inter-hospital collaboration and patient transfers as the outcome of organisational decision. There are 6 papers that are positively associated with organisational performance and patient transfers. All these studies have used relational approach to investigate this phenomenon.

Figure 13: Trend of the study in Inter-hospital collaboration patient transfers



Over the last decade the number of studies in healthcare sector has increased the attention in patient transfers as important part of continuity of care and as well a key element for the delivery of healthcare. This huge literature not only considers inter-hospital patient transfers but also the transfer of patients from one ward to another and the inter-hospital transfer of emergency (critically ill) patients. For instance, the movement of patients among wards, is referred to as intra-hospital patient transfer, or "patient mobility" or "handoffs patients" (Hilligoss & Cohen, 2013; Cohen & Hilligoss, 2010). In general, the impact of these studies on organisation and health literature has grown as shown in figure 7. Keyword searches are: "intra-organisational network"; and "patient mobility" or "handoff" or "sign-out" or "handover" or "report" on SCOPUS returns on 83 papers in total for the period 1984 to 2016 with an average of 2 publications per year. As the graph shows (Fig. 13) over the last three years, a moving average trend-line has been smoothing out fluctuations in this study.

Figure 14: Handoff study trend



In general, intra-hospital patient transfers occur in two ways: 1) when patients are moved from emergency unit to the general ward; 2) when another patient with higher priority required the bed (Watts, Pierson and Gardner, 2005). In a study of intra-hospital patient transfers, the selection of the receiving ward is most likely to be based on the bed-capacity rather than on the performance of the receiving ward. In all these cases, intra-hospital patient transfer is not only reduced to an organisational decision but is regulated by the limitation of time and the number of physicians involved (Hilligoss and Cohen, 2013). Since the intra-hospital transfer is regulated by the lack of coordination among the wards, it may be seen – at physicians and patients' level- as "unpredictable". For this reason, physicians are unsure of actions that need to be taken before and during the transfer (Uhrenfeldt *et al.*, 2013). Consequently, handoffs require regular communication among wards for the best interest of the treatment continuity (Cohen, Hilligoss and Amaral, 2012). On the contrary, inter-hospital patient transfers occur when patients are moved from a hospital with low performance to another one with greater clinical services and wider collaboration network (Assareh *et al.*, 2016). The basic idea behind the inter-hospital transfers is to consider the movement of patients as a part of the organisation plan. This type of transfer is a mere organisational decision, which involves mutual coordination between hospitals. Collaboration between hospitals, created by the patients' flow, shows the decision-making process of hospital organisations in involving others in the care process. Partner selection decision is regulated by taking into account quality of the partners' performance, in terms of capabilities, the location of hospitals and the mutual awareness on the patient transfers (Mascia, Pallotti and Angeli, 2017). In inter-hospital patient transfers, the choice of hospital partner could be seen as a factor in which patients driven decision-making process is not only the result of clinical priorities. In fact, organisational preferences are likely

to be an important factor for the predictability of these transfers. The most important aspect of inter-hospital patient transfer is the continual involvement of partner hospitals in the decision–making process about patients' treatments in such a way the transfer safety is not compromised, and the continuity of care is achieved (Lomi *et al.*, 2014).

Inter-hospital transfers can also involve other types of relation in emergency medicine. It is referred to as "emergency transfers" or "inter-hospital transfer of critically ill patients" (Ribo *et al.*, 2008). This type of patient transfer relation has a high proportion of studies on the overall literature for inter-hospital. Emergency transfers occur in three pathways: i) from the emergency department of the sending hospital to the receiving hospitals; ii) from the ward of the sending hospitals to the receiving one; iii) from an intensive care unit of the sending hospitals to the receiving hospitals (Odetola *et al.*, 2009). In general, the transfer is positively associated with good clinical outcomes, because when hospitals are lacking in capacity and technical capability patients are moved to appropriately resourced hospitals (Iwashyna *et al.*, 2009). Strictly related to the complexity of pathologies and diagnosis of patients, the emergency transfer is sensitive to the timely provision of definitive care for the treatment of the disease (Tranmer, Pallotti and Lomi, 2016). For this reason, this type of transfer has become part of organisational routine and is regulated by formal procedure. Despite the inter-hospital transfer of critically ill patients being automatically performed, the destination is not considered as an outcome of organisational decision-making process because time pressure and the variation of resource consumption are seen as the main factors for carrying out the transfer (Iwashyna and Courey, 2011). Consequently, the selection of the receiving hospitals is not based on the quality of its performance, but on its availability to provide a timely response (Iwashyna, 2012). This involves considering that the emergency patient transfers are not randomly distributed within the hospital network, but it is rather based on proximate, therefore, on the location of the receiving hospitals (Palomeras *et al.*, 2008). This complex transfer is also characterized by the fact that urgency of the case does not give to patients the possibility to accept the clinical and therapeutic paths proposed by physicians (Pallotti, Lomi and Mascia, 2013). Thus, emergency transfers are not "planned transfer" because the decision making-process is affected by the emergency of the case and the need of finding an immediate answer from the receiving hospital. In the inter-hospital patient transfers (or non-emergency transfers), the destination is recognized as an organisational choice in which the lack of emergency and the decision to involve partner hospitals in the care process, demand collaboration between hospitals. Furthermore, in inter-hospital non-emergency transfers, patients are considered as

in-patients or admitted patients (Pallotti and Lomi, 2011). This is an important characteristic of patients because they have already accepted to follow the clinical paths suggested by physicians who have taken the responsibility of their care (Cohen, Hilligoss and Amaral, 2012). The non-emergency transfer occurs only when patients previously admitted to the sending hospital are moved to the receiving one. The therapeutic choice involves a conscious selection of partner hospitals in which the referring hospitals decide who they want to cooperate with.

This research focuses on the patient transfers as form of inter-hospital collaboration and in particular on the transfer of in-patients (or non-emergency transfers). Inter-hospital patient transfers are seen as an important outcome of joint problem-solving arrangements enabling hospitals to coordinate their activities for the solution of common clinical problem (Lomi and Pallotti, 2012). It is important to note that this work is not dealing with the intra-hospital transfers and the transfer of emergency (or critically ill) patients in which the dependence among wards and the hospitals in the case of emergency patients, is regulated by clinical priorities where these type of transfers follow a standardized schema and routine. Consequently, these types of transfers are hardly considered as a simple outcome of decision-making process.

Inter-hospital collaboration aims at ensuring the best possible treatment to patients. Based on this study, table 5 summaries the most cited key relational approach studies in healthcare literature.

Table 5: Key-studies on patient transfers in Interorganisational networks. Note: even if this work is not focused on the emergency transfers, it was relevant to include those studies because the emergency of ill patients comprises 95% of the overall literature

Study	**Theme**	**Country**	**Framework**	**Transfer types**	**Key findings**
Pallotti & Lomi, 2011	Competition	Italy	Inter-organisational networks	Non-emergency transfers	Patients are one of almost an essential criterion to obtain resources from other hospitals because they depend on similar resources (financial resources and patients) and show a very distinctive pattern that support competition

Lomi & Pallotti, 2012	Collaboration	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfers are a sign of collaboration between hospitals, because i)patient transfers promote interactions between doctors by sharing clinical and administrative protocols for managing patient transfers ii) patient transfers represent an outcome of organisational decision that involves a partner hospital to join into a cooperative arrangement
Pallotti et al., 2013	Patient sharing/ networks structure	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfers are a sign of interorganisational collaboration between hospitals that support micro-relational process and give rise to global network structures
Pallotti et al., 2015	Spillover	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfer represents an opportunity for reciprocal learning by sharing clinical information attached with patients who are being transferred. It involves transfer of knowledge regarding clinical and organisational practices of partner hospitals
Lomi et al., 2014	Quality of care	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfer has an implication for patients in terms of high quality of care, because hospitals take decision to move patients from

					less to more specialized hospitals
Tranmer et al., 2016	Embeddedness	Italy	Inter-organisational networks	Non-emergency and emergency transfers	Inter-hospital patient transfer shows a model of coordination associated with the combination of interdependent level of coordination actions at 3 levels (lower level where emergency transfers take place to higher level where non-emergency transfers take place) and this gives rise to a multilevel of network in which hospitals are embedded
Stadtfeld, Mascia, Pallotti, & Lomi, 2016	Decision making process	Italy	Inter-organisational networks	Non-emergency transfers	Patient transfers involve asymmetric relation where sender hospitals assimilate and reproduce experiences of partners (in order to reduce their interdependency); while receiver hospitals try to keep their complementary distinctiveness
Iwashyna et al., 2009	Quality of care	USA	Inter-organisational networks	Emergency transfers	Inter-hospital patient transfers as joint problem solving in order to find a solution to a specific clinical and critical pathway
Iwashyna & Courey, 2011	Critically ill patients/ decision-making process	USA	Inter-organisational networks	Emergency transfers	Inter-hospital patient transfers reflect a therapeutic choice with potential benefits for patient outcomes that could be integrated into clinical decision-making process
Iwashyna, 2012	Quality of care	USA	Inter-organisational networks	Emergency transfer	Inter-hospital patient transfers provide a continuity of medical care in which

					patients' needs and provider's capacity are matched, because technical and physical infrastructure are used by hospitals in order to optimize patient transfers
Odetola et al., 2009	Quality of care/ decision-making process	USA	Inter-organisational networks	Emergency Transfer	By using 3 pathways of inter-hospital transfer from sending hospitals, (ED, ward and intensive care unit) to the receiving one, they find that variation in clinical outcomes and resource utilization depend on the source of transfer. The lack of coordination and the time pressure undermine the positive clinical outcome of transfers at the expense of a high resource utilization.
Ribo et al., 2008	Proximity/ quality of care	Spain	Inter-organisational networks	Emergency transfer	Patients are not always moved into a better hospital. The geographic locations (distribution) of hospitals affect the patient transfers and so the best treatments is not achieved.
Mascia et al., 2017	Proximity/ competition	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfer is related to geographical proximity
Mascia, Di Vincenzo, & Cicchetti, 2012	Governance	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfer represents a form of co-opetition that is included in the governance of healthcare system
Mascia & Di Vincenzo, 2011	Competition	Italy	Inter-organisational networks	Non-emergency transfers	Inter-hospital collaboration is positively associated with hospital productivity. They found that hospital

					performance has negative impact on competition which leads hospitals to collaborate by creating network ties. Relationships are created by the hospitals to foster collaboration.
Assareh et al., 2016	Quality of care/ decision-making process	Australia	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfer represents the coordination arrangements among hospitals. Inter-hospital patient transfers tend to be reciprocated between sending and receiving hospitals. This is considered as an example of routinisation and mutual partnerships. They also find that inter-hospital patient transfer occurs more frequently among hospitals that belong to the same organisational form. It has a positive implication of patients' care, where patients are moved to hospitals with greater clinical services.
Lee et al., 2011	Social networks and Patients sharing	USA	Inter-organisational networks	Non-emergency transfers	Inter-hospital patient transfers as a form of collaboration in which hospitals are interconnected by patient transfers within the health community

All these studies recognize the importance of inter-hospital collaboration and the impact of patient transfers on the organisational performance and the decision-making process. Despite this general recognition, few studies have analysed how patterns of past interaction between hospitals induce local dependencies that may influence future associations over time. This process of endogenous structuration generates the possibilities of observing collaboration

through which hospital organisations are directly connected to each other or to join multiple groups. Collaboration involves information exchange, accumulation of knowledge, and as such provides the source for learning and imitating. As DiMaggio & Powell (1983) suggest in their hypothesis B-1 or A-1 two organisations that are dependent upon a single resource are more likely to perform similarly. Inherent features of patient transfers and inter-hospital collaboration also influence the probability of their association, thus leading to complex patterns and giving rise to core organisational properties such as division of labour, specialization and coordination.

3.5 Data

Data on hospital activities are collected regularly by the Regional Hospital Information System database (SIO), managed by the Public Health Agency of Lazio (Agenzia di Sanità Pubblica – ASP). The SIO released yearly reports on admission of patients aim at evaluating hospitals activities and performance. These annual reports were publicly available from 2006 to 2009. After 2009 the data, although collected, were not publicly available.

SIO information is organized into three different groups. The first group includes the demographic characteristics of each hospital organisation. The second group includes information about the internal clinical specialty of each hospital. The third group includes information on patient transfers among all public and private hospitals organisation in Lazio – which is the network hospital dataset.

The network hospital dataset contains distinct classes of information: attributional and relational information. The attributional information involves information on characteristics of individual nodes in the network, i.e. hospitals. Table 6 reports the organisational variables that has been collected for each healthcare providers.

Table 6: Organisational (monadic) level variables

Variable	Definition	Type	Unit of measure
Hospital code	Code institutionally assigned to hospitals by health authorities	-	-
Organisational form	It considers the hospital's membership to the institutional categories used by health authorities to classify hospitals	Categorical	Nominal
Average length of stay	Length of the average patients 'stay in hospital after admission	Continuous	Ratio
Type of assistance	It considers the level of care provided by hospitals	Categorical	Nominal

LHU membership	It considers hospital's membership to the 12 LHUs in which the region is articulated	Categorical	Nominal
Emergency room	It considers the type of emergency room that each hospital has	Categorical	Nominal
Municipality	Name of the municipality in which each hospital is located	-	-
Staffed ordinary beds	Total number of ordinary beds set up and staffed for use in hospitals. It used in healthcare literature as a measure of organisational size.	Count	Interval
Staffed DH beds	Total number of day hospital beds set up and staffed for use in hospitals. It used in healthcare literature as a measure of organisational size.	Count	Interval
Specialties	Total number of specialties offered by hospitals	Count	Discrete
Emergency admission	Total number of patients admitted via emergency units	Count	interval
Occupancy rate (%)	The percentage of ordinary hospital beds occupied at a given time. It used in the healthcare literature to measure the ability of hospital management to allocate internal capacity both effectively and efficiently. It considered as a measure of operational performance of hospitals. It shows the available capacity utilization used by the hospital.	Continuous	Ratio
Case Mix Index	Composite index used in literature to measure the intensity of resource consumption for patients admitted to a particular hospital during a specific time frame. It measures the average severity of illness for discharged acute care inpatients.	Continuous	Ratio
Comparative Performance Index	Composite index that measures the effectiveness – in terms of length of stay- of a hospital relative to the average effectiveness of a reference set of hospitals with analogous composition of cases treated.	Continuous	Ratio
Readmission rate (%)	Percentage of patients treated who are readmitted in the same hospital for the same pathology within 30 days from discharge. It used in literature to measure the quality of care provided by hospitals.	Continuous	Ratio
Surgical Diagnosis Related Groups (%)	Percentage of surgical DRGs over the total DRGs. It used in healthcare literature to measure the complexity of organisational activities. It shows the complexity of tasks performed by hospitals	Continuous	Ratio
Discharges	Total number of discharged patients over total number of staffed beds	Count	Interval

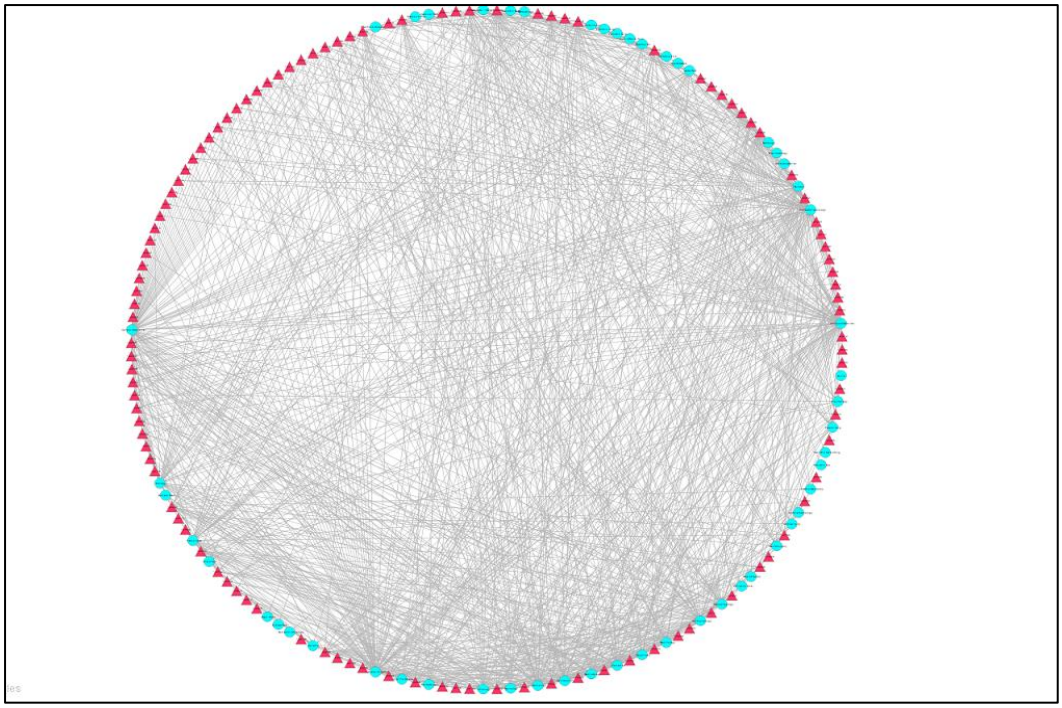
By using the SIO data on attributional hospital organisations, I collected information on the internal structure for each regional hospital, i.e. clinical specialties. Table 7 reports the specialty variables that has been collected for each of the hospitals.

Table 7: Specialty variables level

Variable	Definition	Type	Unit of measure
Specialty code	Code institutionally assigned to hospital specialties	-	-
Specialty name	Name of the specialty	-	-
Ordinary beds	Total number of ordinary beds	Count	Interval
DH beds	Total number of day hospital beds	Count	Interval
Average length of stay	Length of the average patients' stay in each specialty after admission	Continuous	Ratio
Admission from emergency room	Percentage of patients transferred from emergency units	Continuous	Ratio
Ordinary discharged patients	Total number of discharged ordinary patients	Count	Interval
DH discharged patients	Total number of day hospital discharged patients	Count	Interval
DH average admission	Average access in Day hospital	Continuous	Ratio
Case mix index	Average case mix	Continuous	Ratio
Surgical DH	Percentage of surgical DRGs over the total DRGs. It used in healthcare literature to measure the complexity of organisational activities. It shows the complexity of tasks performed by hospitals	Continuous	Ratio

Figure 15 shows the two-mode network of hospitals by the 57 clinical specialties.

Figure 15: Visualization of affiliation networks in Lazio, year 2006. Cyan circle represents specialty; red triangle represents hospital



Examples of clinical specialties contained in the sample are: surgery, cardiology, and neurology. Table 8 reports the five most popular and five least popular activities, together with the frequency of occurrence of hospitals containing them per year. General medicine and general surgery are the specialties that appear 84% over the sample of 110 hospitals.

Table 8: Most and last popular specialties in Lazio

Rank	***Specialization***	***Frequency occurrence (%)***
1	General surgery	84
2	General medicine	84
3	Orthopaedics and Trauma	71
4	Obstetrics and gynaecology	61
5	Cardiology	49
…	…	…
53	Rheumatology	4
54	Oncohematology	2
55	Burns	1
56	Pediatric cardiosurgery	1
57	Allergology	1

The clinical specialties could be seen as the set of capabilities that identify a given hospital. Hospitals may create and change over time their internal set of activities or knowledge pools in response to the input of the environment.

Relational information includes patient transfers among all public and private health providers in Lazio. During the period of observation, 66,076 patients were transferred between hospitals in the sample. I constructed four patient transfer adjacency matrices that include in rows (columns) the hospital sending (receiving) patients, and in intersection cell (vij) the number of patients transferred from row hospital *i* to the column hospital *j* (Wasserman and Faust, 1994). The four matrices are asymmetric because the number of patients sent typically differs from the number of patients received.

Brief note on emergency hospitals and rehabilitation and long-term services

It should be noted that the SIO database reports information about long-term acute care/ rehabilitation hospitals. However, those hospitals have been excluded from the final sample because (i) I focus on elective transfer of patients (in-patients transfer) and not emergency transfers and inpatient rehabilitation hospitals; (ii) they are part of two different branches of the healthcare literature (De Vos et al., 2009) that requires different research questions and analysis as well.

Brief note on not available and missing data

It is important to bring into attention how not available and missing values have been handled. The information used to build this dataset taken from the original SIO database include hospital performance, intensity of resource consumption, and hospital services. Among this information, there are some unavailable values for instance, intensity of resource consumption or occupation rate - if hospitals provide only day hospital services; they cannot have these information about occupation rate or intensity of resource consumption, because they do not have specialized patients or ordinary beds. Regarding the missing values, the dataset contains less than 10% of missing values for some variables and spread about evenly so it was used as the mean imputation approach in order to deal with these missing values.

Brief note on data and methods used for each of the empirical papers

The data used in this study are part of a broader research project funded by the Swiss National Science Foundation (SNF). This study expanded the data collection and built the dyadic. For the first two empirical papers, a dyadic panel dataset has been used, while a whole network dataset has been used for the third empirical paper. For the analysis of the dataset, I relied on the econometric literature, i.e., General Methods of Moments Estimation (GMM) for the first two papers, while I relied on network method, i.e., Stochastic Actor Oriented Model (SAOM)

for the third empirical paper. The table 9 shows the data and methods used for each of the empirical papers.

Table 9: Data and methods for each empirical paper

Empirical Paper	Network Data	Variables	Methodology
Chapter 4 – Empirical paper 1	Dyadic	Dependent variables: Organisational performance – Comparative Performance Index performance differentials Independent Variables: Network-direct ties, tie strength, clique co-membership, structural equivalence and all of them have been raised to power 2	Multiple regression estimated by Generalized Methods of Moment – GMM. The statistical analysis allows to test which network levels is more appropriate for understanding performance similarity
Chapter 5 – Empirical paper 2	Dyadic	Dependent Variable: network variable- patient transfers (tie strength) Independent Variables: geographical distance, structural equivalence (social distance) and interaction effect	Poisson regression with exponential feedback estimated by the GMM. The statistical analysis allows to test the effect of geographical distance on tie strength is moderated by the effect of social similarity
Chapter 6 – Empirical paper 3	One-mode network	Network evolution model (selection) Dependent Variable – Network Independent Variable - Organisational specific determinant of partner selection decisions	Stochastic Actor Oriented Model – SAOM. Combining network measures and organisational variables allows to test for the social processes of social selection and social influence

Chapter 4: Peer effects and inter-organisational performance similarity: A longitudinal study

Abstract

Peer effects occur when the behaviour of an individual is affected by an outside force, such as other individuals. While most of the existing research on peer effects has focused on individuals, less is known about how peer effects actually operate and spread among organisations. At what level do peer effects operate? This paper addresses this question by examining the peer effects at three levels: dyadic, network subgroup, and whole network levels. The objective of this study is to analyse and clarify the most important level for understanding similarities in behaviours among connected organisations. More specifically, this study compares and adjudicates among various competing levels and the related mechanisms that might be responsible for observing similarities in behaviours among connected organisations.

The empirical case is developed around the longitudinal data on patient transfer relationships, collected within a regional community of hospital organisations from 2006 to 2009. Patient transfers are seen as an intense form of collaboration among partner organisations. Similarity in organisational behaviour is computed using the comparative performance index (CPI), an indicator that is frequently used as a measure of organisational performance. I also used the information on a number of organisational and institutional characteristics to assess their role in the peer effects observed among the hospitals in the sample. Analytically, I used the dyadic panel data and multiple regression estimated by the generalised method of moments (GMM). The results provide evidence on how peer effects operate within an inter-organisational context and help to explain the similarities and the differences in the organisational outcomes and behaviours.

Keywords: Peer-effects, social networks, inter-organisational networks, healthcare dataset.

Highlights

- Exploring the existence of peer effects on performance similarity at three different network levels of analysis simultaneously
- Identifying the most important network level for understanding similarities in behaviours among connected organisations
- The strength of direct ties has a non-linear, U-shaped effect on performance similarity
- Network position has a non-linear, U-shaped effect on performance similarity
- Embeddedness in multiple network subgroups has no significant effect on performance similarity

4.1 Introduction

It has been observed, in both economics and social studies, that peers affect individual behaviours, beliefs, and outcomes. Understanding peer influence is important because of the wide range of behaviours that it affects, such as health choices (Fowler and Christakis, 2008), individual performance within classrooms (Sacerdote, 2001), and adoption of new technology (Bramoulle and Kranton, 2005). One of the main theoretical constructs within economic theories that captures the change in behaviour is 'peer effects', which is 'the correlation between outcomes of individuals who interact together' (Bramoullé, Djebbari, & Fortin, 2009:41).

In the existing economics literature, the analysis of peer effects has led to a recurring result: within social groups, there is a strong tendency toward uniformity, i.e. individuals adopt uniform standards of behaviour accepted by their group of peers (Zimmerman, 2003). Peer effects seem to work homogenously across group members, as all the individuals within a group tend to adopt the same behaviour. Betts & Zau, (2004), for instance, utilised the data from the San Diego Unified School district and investigated the influence of peer groups on a student's achievements. They found that students who study with their group members are more likely to assimilate the behaviour of the other group members and improve their grades. The peer group was found to be a strong predictor of the student's achievements in both math and reading. They also showed how changing a student's peer group affected the student's achievements in different settings. Falk & Ichino (2006) found that peer effects make two workers behave similarly by reducing the productivity differentials between them. In these

studies, the role of social connections has not been considered but been assumed implicitly through common membership in groups or co-location at work. The influential paper of Granovetter (1985) was among the first studies to suggest that individual actions are affected by social structures and embeddedness in these social structures. Granovetter (1985:482) stated that the notion of embeddedness empathises on the argument that 'behaviour and institutions to be analysed are so constrained by on-going social relations that to construe them as independent is a grievous misunderstanding'. Indeed, a recent line of economics research has integrated social network analysis to explicitly consider social connections and to explain the peer effects on individual behaviour by accounting for the distribution of connections and the position of the individuals within the network (Jackson, Rogers and Zenou, 2017). For instance, Calvó-Armengol, Patacchini, & Zenou (2009) show how the intensity of peer effects propagates through the position of each individual in a friendship network. They found that the network location accounts for 7% of the increase in the standard deviation of individual academic performances. Using the Addhealth data, Patacchini, Rainone, & Zenou (2017) explore the role of network ties in educational outcomes. They found that peer effects become stronger over time, when friendships between peers last more than a year. Both empirical studies provide a new insight into the measurement of peer effects, by showing that these effects vary across network members and hence, are not homogenous, depending instead on the position of the individuals within the network structures. However, the measurement of peer effects is still considered a difficult task and a challenge (Sacerdote, 2014, 2011; Calvó-Armengol et al., 2009).

Peer effects have also been investigated extensively in organisational networks literature, where scholars have frequently used various terms, such as social influence, contagion, or diffusion, to refer to these effects. Social influence is the process by which outside influences affect the focal entity's behaviour (Im, Mason and Houston, 2007). This entity could be an organisation. The micro-process by which this occurs could be attributed to many factors such as persuasion, conformity, and social learning (Im, Mason and Houston, 2007). Examples include studies on interlocking directors (Mizruchi, 1996), strategic alliances (Gulati, Nohria, & Zaheer, 2000; Gulati & Gargiulo, 1999), and collaborative relationships (Ahuja, 2000a; Powell, Koput and Smith-Doerr, 1996). One of the major theories within organisational theory is the neo-institutional theory; it highlights the importance of mimetic isomorphism, which is a form of social influence (DiMaggio and Powell, 1983). For example, the abandonment of a strategy is contagious because leaders examine what other organisations are doing in order to

better understand when to change their strategy. Greve (1995) analysed how organisations are influenced by their peers in the adoption of new organisational strategies. Using the data of US corporations, Mizruchi (1996) found that organisations adopt the same political behaviour when sharing board members. Fracassi (2016) utilised the data from US public organisations and showed that the more connected the organisations are in the interlocking networks, the more similar is their behaviour in terms of capital investments. In summary, empirical evidences suggest that when peer effects are at work, organisations change their behaviour as a response to the relationships with their network peers through which the resources are channelled. More specifically, once established, peer effects lead organisations to behave similarly; in other words, organisations are more likely to adopt similar practices (Davis and Greve, 1997) and develop similar strategies and behavioural orientations (Galaskiewicz and Wasserman, 1989). This happens because peer effects provide the '*relational infrastructure*' to support a range of processes, including learning (Powell, Koput and Smith-Doerr, 1996), assimilation and differentiation (Stadtfeld *et al.*, 2016), competition (Burt and Talmud, 1993), imitation or diffusion (Greve, 1996), and influence (Liu and Srivastava, 2015). These processes represent the actual mechanisms through which peer effects operate among individuals, groups, or organisational communities. For example, Mizruchi & Marquis (2006) used the data from US political corporations and showed how social influence operates at different network levels from the dyadic level to the system network level. They found that organisations are influenced by their peers at the dyadic level, where direct relationships between organisations make network partners more similar. However, there is still less insight into the range of how peer effects operate and lead to behavioural similarity (Pallotti, Tubaro, & Lomi, 2015; Mizruchi & Marquis, 2006; Mizruchi, 1993).

Building on the works of Mizruchi & Marquis (2006) and Pallotti et al. (2015), in this work, I extend the prior research on peer effects and IONs in two ways. First, by using a longitudinal design, I investigate how peer effects operated over time. More specifically, I compare and contrast the magnitude of peer effects at the dyadic, subgroup, and network levels to understand the behavioural similarity among organisations. Prior research has emphasised the importance for future research to use a longitudinal framework to investigate the dynamics of the peer effects and the behavioural similarity over time (Pallotti, Tubaro and Lomi, 2015). The aim of this research is to clarify and analyse the most appropriate level for understanding the behavioural similarity among organisations over time. I used peer effects as a mechanism that led the social influence, diffusion or contagious processes. These processes could be seen as

the possible outcomes generated by the existence of peer effects at work, whereby the connected organisations became progressively similar in terms of their behaviour over time (i.e. social influence). Second, the aim of this research is to show how peer effects are unevenly spread in IONs depending on the patterns of connectivity and position similarity in which the organisations were embedded. More specifically, I compare and adjudicate among various competing levels and the related mechanisms that might be responsible for observing the behavioural similarities among the connected organisations. Prior research has shown that peer effects are unlikely to be homogeneous depending on the pattern of relationships in which the organisations are embedded (Patacchini et al., 2017; Calvó-Armengol et al., 2009). In this work, the similarity in performance between interconnected organisations is measured as a performance differential. This is in line with the idea that behaviour is the outcome of whatever flows through relationships (information and/or resources). Hence, peer effects are associated with the reduction of the performance differentials between the connected partners (Lomi *et al.*, 2011). In this work, I use the dyad as the smallest unit at which the peer effects could be detected (Stuart, 1998; Calvó-Armengol, Patacchini and Zenou, 2009).

Therefore, the main research question that this work attempted to address is as follows: in an inter-organisational context, *at what levels are peer effects more likely to operate?*

By answering this question, this paper bridges the economics literature on peer effects and the social networks literature on the simultaneous use of different network levels to the extent to which organisations behave similarly.

The empirical setting is an ION where the relationships were particularly relevant as a vehicle to gain exposure to learning opportunities and to access valuable extramural resources and information (Powell, Koput and Smith-Doerr, 1996; Gulati and Gargiulo, 1999). In particular, I use the longitudinal data of patient transfer relationships established among hospital organisations from 2006 to 2009. Prior works have documented that patient transfers involve an exchange of information between hospitals and this information is channelled through certain relationships (Iwashyna, 2012). A patient transfer is considered a proxy of collaboration between the partner hospitals (Lomi and Pallotti, 2012). As I will explain later in this paper, a patient transfer represents a physical trace of the coordinate arrangement created to support the inter-organisational collaboration between partners involved in the transfer.

The rest of this paper is organised as follows: Section 4.2 provides an overview of the relevant literature on the peer effects in both economics and IONs, and of the available research on the

relationship between the peer effects and the performance similarity. Section 4.3 describes the research design and data. The estimation of the empirical model is discussed in Section 4.4. Section 4.5 describes the results. Section 4.6 concludes the paper by discussing the findings and by outlining the potential directions for future research.

4.2 Theory and Hypotheses

In the following section, I will discuss the hypotheses about peer effects and inter-organisational peer networks. More specifically, the literature review starts by explaining the role of peer effects on individual outcomes in economics (subsection 4.2.1). The next subsection explains the role of peer effects on organisational outcomes in inter-organisational networks (4.2.2). The final subsection presents the hypotheses based on literature discussing peer effects at different network levels (4.2.2.1).

4.2.1 Peer effects and individuals

Until recently, peer effects were inferred by looking at the association among individuals, by only assuming the existence of an underlying ongoing relation supporting the transfer of knowledge, information and resources (Sacerdote, 2014). Peer effects have been investigated by looking at how 'an individual's response to peer's behaviour may vary by peer type, i.e. males versus female, white versus black, etc.' (Patacchini et al., 2017:191) or by context, i.e. co-location in the same workplace (Falk and Ichino, 2006). For example, using data on roommates from two different institutional settings, Griffith & Rask (2014) estimate peer effects by looking at the impact of different attributes of their peers like race, income and gender on educational outcome. They find that peer effects are stronger across males, minorities and aided students. However, results based only on the properties of peers do not tell the complete story about the existence of peer effects because the literature suggests 'that we do not yet know enough about the nature of peer effects' (Sacerdote, 2014:269).

More recently, scholars started using social network analysis. According to Montgomery (1991) changes in behaviour might be better explained by taking into account connections between actors to explore if well connected actors perform better than those who are not well connected. For instance, using longitudinal data from Tel Aviv school dataset, Lavy & Sand (2015) investigate peer effects by looking at the influence of social networks on student's outcomes, (i.e. reciprocated ties). They find that the number of friends and the characteristics

of peers influence students' performance, depending on the type of ties in the short and long run. Using a sample from the National Longitudinal Survey of Adolescent Health data, Dieye & Fortin (2017) investigate the effects of friendship ties with male versus female peers on individual's weight outcomes. First, they test the formation of network ties and its effect on Body Mass Index. They find that actors tend to be influenced by their peers. Second, they estimate a model that allows for both the presence of isolated actors (students in their case) and gender-dependent heterogeneity. They find positive and strong peer effects associated with white female students but no peer effects associated with white male students. Using data on friendship networks from the National Longitudinal Survey of Adolescent Health Data, Patacchini et al. (2017) show how peer effects tend to vary according to two types of network ties established by students. First, *long- lived ties* in which students nominated their peers over a period of time, consequently, ties are renewed at different time points; and second, *short-lived ties* where students nominated their peers at one time period, hence ties are cut off. They find positive and significant peer effects for students who interact repeatedly, while peer effects are not statistically significant in those cases where students interact each other only at one point in time. They suggest that long social interactions appear to be more important to foster education. Using a sub sample of the same data Calvó-Armengol et al. (2009) estimate peer effects through the structure of friendship network to explain individual outcomes. They find that the network location has an impact on individual outcomes.

In summary, these studies show the importance of accounting for network structure (i.e. nature and types of relations) for understanding individual' behaviours and outcomes (for a recent literature review, see Jackson et al., 2017). Different network indicators have been used to estimate peer effects, such as degree distribution, (Jackson and Rogers, 2007), clustering (Graham, 2014), centrality measures (Bloch, Jackson and Tebaldi, 2017), density (Colizza and Vespignani, 2007). The economics literature, however, has three limitations. First, while most research has focused on individual's characteristics where peer effects arise only from the location and hence the measurement of peer effects were unclear, until recently the role of social relations have been considered explicitly for explaining peer effects. Second, while most research has been conducted on peer effects among individuals, far less attention has been devoted to the role of peer effects in explaining organisational behaviour. Third, while the importance of networks on individual outcomes has been well recognized, empirical studies currently focus on only one level of analysis, such as dyadic or group (for a recent literature review, see (Sacerdote, 2014; Durlauf, 2004;). To the best of my knowledge this is one of the

few studies looking at peer effects in organisational settings and comparing their effects at different levels. As I explained in Chapters 1-2, organisations are composite social agents where various social interactions take place among organisations. It is therefore reasonable to assume that most of the social processes at work in organisation and between organisations - such as learning, peer pressure, and influence- are the result of peer effects operating through those interactions. Also, when peer effects have been investigated in organisational settings they have been examined by focusing mainly on one single level (i.e. dyad and group). Because peer effects may propagate at different network levels and not just at a single level of analysis (Pallotti et al., 2015; Mizruchi & Marquis, 2006), this work investigates peer effects at network levels simultaneously. Following the definition of peer effects, I examine peer effects among organisations by looking at similarity in organisational performance. I also identify the level at which similarity among interconnected organisations are more likely to occur.

4.2.2 Peer effects and organisations

According to Galaskiewicz & Wasserman, (1989:456) 'if two actors have direct and indirect relationships with one other, they are more likely over time to think alike or behave similarly'. Therefore, social networks provide a relational context through which information, opportunities, constraints are channelled and affecting organisational behaviour and outcomes. These relationships influence the flow of information (Ahuja, 2000b), resources and capabilities (Gulati and Gargiulo, 1999), knowledge (Tortoriello, Reagans and McEvily, 2012), and consequently the extent to which organisations behave similarly (Mizruchi, 1993). Galaskiewicz & Burt (1991), for instance, use data from non-profit organisations, to show that peer effects operate more strongly at network level. More specifically, organisations that occupy network positions and share a large partner show much similar behaviour. This is because inter-organisational relations spread practices and facilitate information spill overs (Owen-Smith and Powell, 2004) whereby peers are lead to a shift in organisational orientation, behaviour and performance. Many empirical studies show that membership in subgroups allows organisations to be exposed by peer pressures (Rowley *et al.*, 2004), e.g. pressure to assimilate or differentiate from the behaviour of their peers. For example, using political data, Liu & Srivastava (2015) analyse the interactions between political groups on voting behaviour. They find that peer effects within groups lead to similarity in political behaviour as the consequence of interactions between peers. They also find that social relationships foster differentiation processes whereby actors who belong to different political parties are more

likely to change their voting behaviour. These studies suggest that similarity in behaviour is the result of the way social actors are embedded in network of relationships, where peer effects can be understood by considering the connection of social actors in the network (Mizruchi, 1993). 'Thus, the embeddedness of the firm in a network of inter-organisational relationships sheds additional light on how and why firms act and perform the way they do' (Zaheer, Gözübüyük, & Milanov, 2010:63).

Although the prediction of similarity in behaviour and attitudes has been an important goal for inter-organisational scholars, many of the existing empirical studies only use one level of analysis to investigate peer effects (Baum, Rowley, Shipilov, & Chuang, 2005; Haunschild, 1993; Davis, 1991). Therefore, a recent stream of literature has started to explore social influence by taking into consideration network levels. In their work, Mizruchi & Marquis (2006) argue that embeddedness of organisations in social network structures enables and constraints the organisational behaviour. More specifically, they test for the existence of social influence by looking at performance similarity and by measuring influence at different levels. Using dyads as the smallest unit of analysis at which social influence can be detected, they show that inter-organisational similarity depend on embeddedness of organisations in dyadic relations, in network clusters and their position in the network as a whole. The importance of accounting for different network levels are related to the fact that these three levels correspond to specific social influence processes involving from local to larger sub-sets of network. The first level (direct social interaction) is associated with strictly dyadic mechanisms involving only one organisation and its immediate partners. The second level (network subgroups) is intermediate and is associated to mid-range mechanisms of cohesion associated with membership in overlapping cliques. The third level (jointly occupied positions) is associated with positional mechanisms of structural equivalence and involves therefore a global range associated with network positions in the network as whole.

Understanding the different mechanisms, it is relevant because the internal relational structures in which organisations are embedded is not homogenous whereby similarity in behaviour spreads by direct or indirect peer influence. Therefore, the investigation between social relations and peer effects requires the analysis of what has been called 'inter-organisational peer networks' (IOPNs) – which brings differentiated benefits to their members (Sgourev and Zuckerman, 2006; Zuckerman and Sgourev, 2006). IOPNs provide a particular example of how organisational outcomes are affected by networks of collaborative relations in which organisations embed their actions (Granovetter, 1985). IOPNs affect the behaviour and

performance of organisations by facilitating access to extramural resources 'aimed at achieving higher performance' (Zuckerman & Sgourev, 2006:1330). Furthermore, IOPNs provide opportunities to learn from the experience and capabilities of peer organisations (Sgourev & Zuckerman, 2006). Accordingly, the expectation is that peers influence organisations in a way that organisations actually learn from them (Beckman and Haunschild, 2002) and will eventually yield higher levels of performance. If this expectation is generally observed, then the aggregate consequence is that performance differentials among members of an IOPN will necessarily decrease as the consequence of the existence of peer effects (Pallotti, Tubaro and Lomi, 2015). This is directly relevant to my current purpose. The social embeddedness perspective that inspires this work also offers a coherent theoretical account for the role of peers effect at: (i) the dyadic level, e.g. dyadic relations and its strength with direct network partners, (ii) network subgroups, e.g., membership in network cliques, and to (iii) network positions, e.g., positional similarity in the network as a whole. This is aligned with the recent debate on inter-organisational literature and similarity in behaviour, e.g. peer effects. Table 10 provides a summary of existing literature of peer effects in IONs, where only few empirical studies currently have investigated the outcomes of peer effects, e.g. behaviour similarity among organisations at multiple network levels simultaneously. This calls for further development.

Table 10: Inter-organisational networks and peer effects. Representative sample of key-studies on inter-organisational networks and peer effects[3].

Author(s)	Year	Evidence of peer effects	Level of analysis	Research design	Findings
Friedkin	1984	Influence & Similarity processes	Dyadic level	Cross-sectional	Direct and short indirect relations are component of cohesion and they foster assimilation process. Structural equivalence is not a strongly indicator associated with the level of similarity in the network. The pattern of structural cohesion within and between groups in a network is associated with the level of similarity in the network
R. S. Burt	1987	Influence & Similarity processes	Joint effects of multiple network levels –	Cross-sectional	Social influence works strongly at global network level, where social actors are more exposed to peers pressures and start to adopt the same behaviour of their peers
Galaskiewicz & Wasserman	1989	Influence & Mimetic processes	Dyadic level	Longitudinal	Organisations are more likely to emulate the behaviour of the other organisations to which they have interpersonal relation via boundary-spanning activities
Galaskiewicz & Burt	1991	Influence & Mimetic processes	Network level	Cross-sectional	Organisations that occupy the same network positions share the same evaluation pattern because of peer effects. More specifically, organisations- that jointly occupy the same

[3] Note: Even if the papers are not very recent, it was relevant to include those studies because they represent key-studies and the status quo on this subject.

					network positions - are guided in their evaluations by the opinion of their same peers rather than the opinion of organisations with whom they are directly connected to
R. Burt	1992	Influence & Imitation processes	Network level	Cross-sectional	Social influence spreads through the position that organisations occupy within the network as whole. Organisations that occupy the same network positions are more likely to feel peer pressure and assimilate the behaviour of their peers. When organisations are directly connected to their peers, they do not display similar behaviour
Mizruchi	1993	Influence process	Dyadic level	Cross-sectional	The strength of direct social ties, structural equivalence and role equivalence are associated with similarity in political behaviour. However, role equivalence is the consistent indicator of similarity in behaviour, when controlling for the levels of cohesion and structural equivalence. More specifically, he finds that the more prominent two firms are, the more likely they are to behave similarly
Harkola & Greve	1995	Influence & Mimetic processes	Network level	Longitudinal	Cohesion triggers mimetic process in higher density network, whereas structural equivalence affect diffusion in low density networks
Powell et al.	1996	Learning process	Network level	Longitudinal	There is a positive correlation between peer effect and innovation: organisations that are well- connected within the network are more likely to learn and perform better. Peer effects support learning processes whereby organisations acquire knowledge and increase their performance
Uzzi	1996	Influence & Assimilation processes	Ego level	Cross – sectional	Social influence operates more strongly at dyadic level, but high or low level of embedded ties are positive up to a threshold point. When peer pressure is high then organisations tend to change their behaviour and differentiate their strategies
Uzzi	1997	Influence & Competition process	Dyadic level	Cross-sectional	There is a non-linear relationship between economic performance and social influence by showing that the positive effect of the embeddedness rises up to a threshold after which over-embeddedness makes organisational performance decrease and it consequently triggers competition process
Davis & Greve	1997	Influence process	Ego level	Longitudinal	Peer effects operate at dyadic level by showing that an influence process spreads rapidly through boards. Furthermore, organisations that have higher level of centrality are more likely to influence the others
Kraatz	1998	Imitation & Learning processes	Dyadic level	Longitudinal	Organisations that directly connected with each other are more likely to adopt their orientation in terms of professional degree programs in accordance with the experiences of their peers. Colleges tend to imitate the strategy of their peers as being influenced by information received through social ties. The chance of imitating a particular professional program were influenced of early adopters of that program as they learn from their peers especially when some external factors is ongoing

Hedström, Sandell, & Stern	2000	Influence & Imitation process	Clique level	Longitudinal	Social influence operates at clique level; where peers promote an imitation process, in a way that the members imitate their reference group as a consequence of the existence of peer effects. Peers trigger the diffusion of political practices within network subgroups. At dyadic level peer effects is weakly significant and weakly support influence process. This means that being connected is one criterion to examine peer effects but not necessarily leading to influence and imitation
Ahuja	2000a	Learning & Influence processes	Ego level	Longitudinal	Social influence operates more strongly at dyadic level by showing that direct and indirect ties are positively correlated to peer effects (innovation output), where the effect of indirect ties is moderated by the organisation's level of direct ties. Structural holes are negatively correlated to peer effects, as an increase in structural holes in the inter-organisational collaboration networks corresponds to a reduction of innovation output
Tim J Rowley et al.,	2004	Influence & Competition process	Clique level	Longitudinal	Peer pressure operates only within groups where members assimilate the behaviour of their peers and attain same level of performance. However, the position of the groups within the network does not affect organisational performance
Timothy J Rowley, Greve, Rao, Baum, & Shipilov	2005	Influence& Assimilation process	Clique level	Longitudinal	Peer pressures operates within network subgroup, where members are more likely to assimilate the behaviour of their reference group
Singh	2005	Learning process	Network level	Longitudinal	There is a positive correlation between direct and indirect ties and peer effects. However, organisations that are connected only through indirect peers or that are isolated do not acquire knowledge
Zaheer & Bell	2005	Influence process	Ego level	Cross sectional	Social influence operates at global level by showing that focal organisation perform better when they occupy "a superior network position". They also find a positive correlation between peer effect and structural holes. Where organisations occupy a structural holes position, they are more likely to enhance their individual performance
Mizruchi & Marquis	2006	Influence & Behaviour similarity	Joint effects of multiple network levels	Cross-sectional	Social influence is more strongly at dyadic level of analysis, where peer effects do not allow a prediction of similarity in behaviour at meso and macro levels
Pallotti et al.,	2015	Assimilation & Learning processes	Joint effects of multiple network levels	Cross-sectional	Social influence operates stronger at global and meso level, while they do not operate at micro level. Furthermore, there is a non-linear effect between peer effects and joint membership in cliques

4.2.2.1 Inter-organisational peer networks and network levels: dyadic; network subgroups and whole networks

Peer effects among organisations have been investigated in different settings, for example university organisations (Kraatz, 1998); manufacturing organisations (Mizruchi, 1993); chemicals organisations (Ahuja, 2000a); and hospital organisations (Pallotti, Tubaro and Lomi, 2015). Research on this topic has assumed that peer influence spreads primarily through dyadic relations between organisations (Mizruchi and Marquis, 2006). Direct ties bring benefits to organisations i.e. knowledge transfer and complementarity. First, direct ties enable organisations to acquire new knowledge and making resources available to partners (Ahuja, 2000a). Organisations that have direct relations can obtain a greater amount of resources from their partners in comparison to those working independently. Second, direct ties bring complementarity resources from different organisations in order to achieve a common goal (Powell, Koput and Smith-Doerr, 1996). Because information, knowledge speed through relations, it is therefore only reasonable to assume that peer effects operate at dyadic level making organisations more similar in terms of behaviour orientation and outcomes (Kraatz, 1998). The tendency of organisations to become more similar to their partners also depends on the strength of direct relations. Strength ties speed up the diffusion of resources and knowledge, as the frequency can promote a depth exchange of detailed information and enable trust about partners (Uzzi, 1996). As strength of ties are characterized by a greater degree of trust and cooperation, they increase awareness about the reliability of their partners whereby reducing costs and risks associated with the transfer. Indeed, 'trust and mutual identification that are likely to exist when ties are strong make it more likely both that organisations will share valuable information provided will be taken into account and acted upon' (Kraatz, 1998:623). In other words, as strength of ties allow organisations to access valuable information that are particularly critical in the context of inter-organisational collaboration, organisations will adjust their behavioural orientations to conform to the expectations of their peers. Consequently, the propensity of two interconnected organisations to perform similarly will be higher. However, extant inter-organisational research seem to agree only partially about the precise implications of the strength of social relations on performance similarity. An alternative view suggests that strength of ties reduce the flow of new information as a consequence of redundancy (Burt, 1992). Because strong relations depend on trusted partners and hence necessitates more maintenance and consequently are more likely to have less information flows (Kraatz, 1998). In other words, bilateral exchanges increases the frequency and the number, the redundancy of information becomes higher. As strength gradually destroys the probability of new information to be received (Rogers, 1995), the propensity of two connected organisations to perform similarly will be lower, where peer pressure becomes less intense as

the same information is already channelled through similar partners. In sum, as the strength of social relations increases, two organisations will quickly assimilate knowledge of their peers (Ahuja, 2000a), though at a decreasing rate. As similarity increases two organisations will be more likely to have redundant information and knowledge assimilation will decrease at an increasing rate. This argument suggests a U-shaped relationship between the strength of social relations and performance similarity. Based on the above, the first hypotheses are:

Hypothesis 1.a: There is a positive relationship between direct ties and similarity in performance between organisations.

Hypothesis 1.b: There is a positive relationship between the strength of ties and similarity in performance between organisations.

Hypothesis 1.c: There is a nonlinear relationship between the strength of ties and performance similarity between organisations. As the strength of collaboration between two organisations increases, similarity in performance will increase up to a point after which similarity in performance will decrease.

The dyadic level is not the only level at which peer effects can be examined. As a matter of fact, empirical research shows that organisations tend to cluster together, i.e. to form groups of highly connected organisations (Rowley *et al.*, 2004). It is therefore only reasonable to assume that peer effects also operate within subgroups. In other words, there might be a tendency of organisations within subgroups to perform similarly. The study of peer effects between organisations in subgroups has been conducted in various settings, for example the banking industry (Rowley *et al.*, 2004); political parties (Hedström, Sandell and Stern, 2000); and school district organisations (Friedkin, 1984). Subgroups are characterized by strong elements of cohesion that lead members to change their behaviour in accordance to the cooperative norms established by the group (Rowley *et al.*, 2005). Therefore, relations within subgroups are considered to push more pressure on the members and to conform to the norms whereby increasing similarity in terms of behaviours and attitudes (Prell, 2012:151). Within the subgroup, organisations depend on evaluation by the same members, and consequently, will align their behavioural orientation to conform to the members' expectations (Friedkin, 1984). Members 'within subgroups have a higher incidence of face to face interaction and a larger number of short communication channels between them. Accordingly, members within subgroups are predicted to be more homogenous in terms of attitudes and behaviours' (Friedkin, 1984:237). However, empirical studies suggest that relations within network

subgroups became “saturated” as organisations are connected to the same members and share the same resources, thus reducing the capacity to absorb new information (Burt, 1992). Consequently, relations within network subgroups come to be over-embedded and organisations start to adopt different strategies (Uzzi, 1997). For instance, Pallotti et al. (2015) show that the effect of peers at network subgroups increases performance similarity of two connected organisations at a limit point. Once this limit point is achieved, two connected organisations are more likely to perform differently. This argument suggests a U-shaped relationship between network subgroups and performance similarity. Based on the above, the second hypotheses are:

Hypothesis 2 a.: There is a positive relationship between membership in network subgroups and similarity in performance between organisations.

Hypothesis 2 b.: There is a nonlinear relationship between performance similarity and membership in network subgroups. As two organisations share membership in the same network subgroups, similarity in performance will increase up to a point after which similarity in performance will decrease.

Finally, peer effects can be detected at network level (Mizruchi and Marquis, 2006). The study of peer effects at network level has been conducted in different settings and affects a wide range of relevant organisational outcomes, for example the adoption of competitive strategies (Greve, 1996); corporate practices (Davis and Greve, 1997); and behavioural orientations (Galaskiewicz and Wasserman, 1989). This view relies on the concept of structural equivalence that is, organisations with a similar network position to another will have similar resources and constraints, and thus leads to behave similarly (Burt, 1987). Therefore, it is only reasonable to assume that peer effects work also at network level. Two organisations behave similarly because they are likely to imitate the actions of their peers that are perceived to be in similar positions of resources dependence (Zaheer & Bell, 2005; Harkola & Greve, 1995). In fact, positional similarity or network positions are considered as the main sources of influence affecting organisational performance (Burt, 1987). Galaskiewicz & Burt (1991) find that structurally equivalent organisations are guided in their valuations by the opinion of their same peers rather than the opinion of organisations with whom they are directly connected to. As a consequence peer effects, organisations will share the same evaluation and same organisational behaviour. Network position is also considered a source of competition, because structurally equivalent organisations depend on common resources controlled by the same group of alters.

This leads organisations to compete (Mizruchi, 1993; R. Burt, 1992; R. S. Burt, 1987). In other words, network positions increase competitive constraints and peers pressure become more intense. As competition gradually destroys social ties (Burt, 1992), the propensity of two connected organisations to perform similarly will be lower, where the intensity of competition is higher. In sum, as positional similarity increases, two organisations will quickly adopt the successful experience of others who occupy similar network positions with respect to resource dependencies (Burt, 1992), though at a decreasing rate. As similarity increases two organisations will be more likely to compete for the same resources and peer pressure will increase at an increasing rate (Burt, 1987). This argument suggests a U-shaped relationship between network positions and performance similarity. Based on the above, the third hypotheses are:

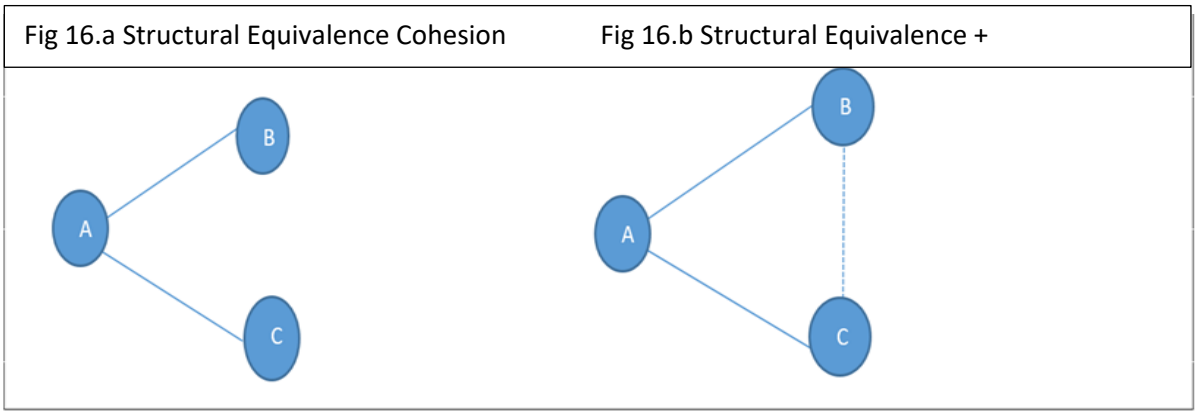
Hypothesis 3.a: There is a positive relationship between network position and similarity in performance between organisations.

Hypothesis 3.b: There is a nonlinear relationship between network position and similarity in performance between organisations. As two organisations occupy similar network positions, similarity in performance will increase up to a point after which similarity in performance will decrease.

Discussing peer effects at different network levels and related mechanisms that may be responsible for observing similarity in behaviours among connected organisations, it also allows the consideration of two types of network structures that result in peer influence, i.e. cohesion and structural influence. These all-connect networks in a different ways, where two social actors interact with each other, i.e. cohesion; and structural influence where two social actors are in similar structural positions in the network although they do not necessarily interact with each other (Marsden and Friedkin, 1994). In this view, similarity in behaviour can be associated with the idea of social proximity, or information between egos and alters, where cohesion explains behaviour similarity ‘fostered by face-to-face interaction and short communication channels through intermediaries’ (Friedkin, 1984:237). On the other hand, structural equivalence explains behaviour similarity where social actors ‘do not require face to face interaction; indeed, the only precondition for social influence is information (which allows social comparison) about the attitudes or behaviours of a reference group of similar others’ (Marsden & Friedkin, 1993: 128-129).

Likewise, in R. S. Burt's (1987) re-examination of the diffusion of medical innovations he indicates that when two social actors are proximate their decision to adopt new innovation are influenced by other. Burt examines the meaning of proximate in two different ways, that are cohesion and structural equivalence. It is therefore possible to assume that structural equivalence and cohesion may interact together in explaining peer influence. The picture 16.b (Fig.16.b) shows the case where structural equivalence and direct relation interacts with each other.

Figure 16: Structural equivalence + Cohesion



This argument suggests the interaction effect of cohesion and structural equivalence on behaviour similarity. For high and low levels of structural equivalence, similarity in behaviour of disconnected and structurally equivalent organisations are lower compared to connected organisations. Based on the above, the fourth hypothesis is:

Hypothesis 4: Direct connection moderates the U-shaped relationship between network position and performance similarity between organisations, such that the magnitude of the effect of network position on performance similarity will be stronger for disconnected organisations.

4.3 Research Setting and Data

4.3.1 Setting

The opportunity to demonstrate the empirical value of my hypotheses is provided by a longitudinal dataset collected on hospital organisations over the period 2006 to 2009. The hospitals provide healthcare coverage in Lazio- one of the largest Italian regions with a

population of roughly 700,000 inhabitants, distributed over approximately 6.657 square miles. Lazio is organized into five urban areas: Viterbo, Rieti, Latina, Frosinone, and Rome, the capital city. I focus on healthcare setting for three reasons: first, hospital performance is well-documented and allows testing for the existence of peer effects among hospitals. The Regional Health Agency also provided access to data on patient transfer relations that I use to measure collaboration between each and every pair of hospitals in the Region. Second, sources of high quality information are available and publicly accessible which provide information and useful knowledge for the government and management of the regional health system. Third, hospitals operate in technical and institutional environments (Scott and Meyer, 1983) in which the survival of hospitals depends critically on their ability to satisfy performance expectations of multiple stakeholders. Hospitals are held accountable for their outcomes; therefore, they must garner legitimacy and obtain support from external constituencies. Hence, collaboration and competition are relevant organisational processes connected to the hypotheses of this work.

Lazio healthcare system is part of the Italian National Healthcare System organized at local, regional and federal levels, where much of health activities and planning are set by the Local Health Units (LHUs). There are 12 LHUs, with 8 LHUs concentrated in the capital city and 4 LHUs covering the remaining urban areas of the Region. LHUs are monitored by the Region and they are administrated by managers whose compensation is performance–based. Two main aspects characterize these units: first, they deliver healthcare services through public and private providers. Second, hospitals differ in terms of size and clinical specialties offered as human and financial resources are not equally distributed across the 12 LHUs. This point is relevant because patients have the freedom to choose any hospital located within and outside their LHU of residence and region.

I focus on collaborative relations established among hospitals through patient transfers. As discussed in chapter 3 - *Empirical setting and data*- , patient transfers are considered as one of the most common forms of inter-hospital collaboration (Amati, Lomi, Mascia, & Pallotti, 2019; Lomi & Pallotti, 2012; Lee et al., 2011). Patient transfers is the result of intense communication and transferring information on best clinical practices between partners (Iwashyna *et al.*, 2009; Iwashyna, 2012), whereby the goal of transfers is to guarantee the best treatment to patients (Lomi *et al.*, 2014). In other words, patient transfers rely on collaboration between sender and receiver hospitals, the execution of the transfer requires coordination between partners as well as resources sharing. In particular, two types of resources are channelled: clinical information and financial resources. Clinical information concerns information about treatments that

patients receive. Financial resources concern the reimbursement that receiver hospitals will receive for treatments provided to patients. I focus on in-patient transfers, i.e. patients who are already admitted before the transfer (Lomi and Pallotti, 2013).

4.3.2 Data

The data are collected from archival sources contained in the regional hospital information system database (SIO), which was described in chapter 3. The data include annual reports from 2006 to 2009 for all hospitals in Lazio. The dataset includes attributes and relational variables collected at the level of each hospitals (private and public hospitals). The first set of variables involves information on properties of hospitals in the network, i.e. hospital performance, number of staffed beds, number of discharges etc. The second set of variables involves information on relation or connections, measured at the level of pairs of hospitals, i.e. patient transfers. The sample for this longitudinal data is n=110. During the period under investigation, some hospitals closed or came into existence, and this makes the data a longitudinal unbalanced panel. The first two waves contain 110 hospitals, the third contains 107 hospitals, and the fourth contains 103 hospitals. Table 11 shows the total number of relationships for each year.

Table 11: Years, and Corresponding relationships

Years	Time Periods	Number of relationships	Number of hospitals
2006	1	2230	110
2007	2	2194	110
2008	3	2027	107
2009	4	2027	103

Relational data were managed by entering the value, i.e. number of patients transferred in four adjacency matrices. Because the inter-organisational network induced by patient transfer relations is asymmetric, the final sample consists of 45,828 dyads over the period 2006-2009. Table 12 shows the main descriptive statistics of the analysed networks. The table 12 also shows a decreasing number of patient transferred over time, this is due to the fact that some hospitals could have closed and thus impacts the intensity of collaboration among hospitals at the regional level as seen empirically in this case.

Table 12: Network Statistics

Years	Time Periods	Number of dyads	Number of patients transferred
2006	1	11990	18175
2007	2	11990	16557
2008	3	11342	15757
2009	4	10506	15577

4.3.3 Variables and Measures

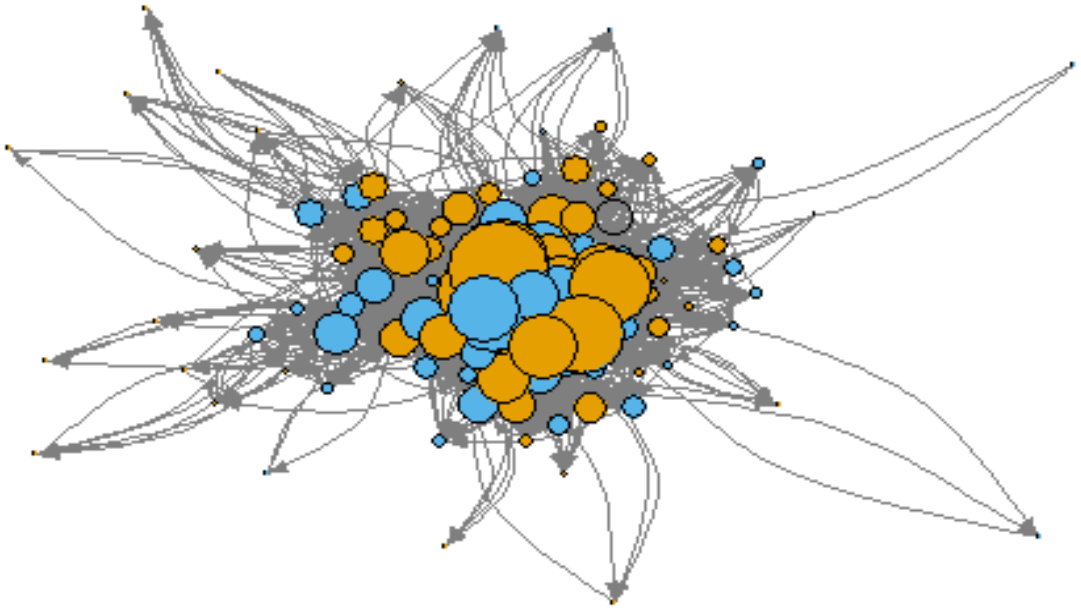
4.3.3.1 Network Measures

Since I was interested in the presence of patient transfer relations, I dichotomized the inter-organisational network to compute the two main variables of theoretical interest, namely network subgroups (clique co-membership) and network position (structural equivalence). If two hospitals have shared at least one patients, a relational tie is present between them (Pallotti et al., 2015; Lomi & Pallotti, 2012; Lee et al., 2011). I have decided to apply this simple dichotomization rule ($xij = 1$, if $vij \neq 0$), to integrate all providers involved in the transfers of patients and to avoid differentiating between strong and weak ties (Pallotti et al., 2015; Lomi & Pallotti, 2012). I appreciate that there are various ways for dichotomizing the network for example, using the mean value as cut-off point or applying relative threshold rules like including the top 10% , 20% or 30% for defining a relation. However, there is no a uniform procedure which establishes "true" relationship and reliably excludes randomly appearing ones (Brunson & Laubenbacher,2018). My aim was to derive a complete network including all relevant social actors and their relationships.

On the other hand, I used the valued network (i.e. the number of patient transfers) to compute the third main variable of theoretical interest, that is tie strength. Following previous research (Pallotti et al., 2015; Gittel, 2002) the number of patients transferred between two hospitals captures the intensity of collaboration. My aim was to derive a valued network reflecting the strength of a relationship between social actors.

An illustrative graphical representation of the inter-hospital patient transfer networks is provided in Figure 17. Hospitals are represented as nodes and patient transfers represent relations among hospitals. The size of hospitals is related to their number of patients transferred (degree) and their colour is related to their level of performance as measured by the Comparative Performance Index (CPI): orange for hospitals whose CPI is higher than 1, blue otherwise.

Figure 17: Inter-hospital patients transfer networks



4.3.3.1.1 Independent Variables

In this section, I will describe and define the main variables of theoretical interest that are included in the model specification.

Tie Strength. This variable is measured by the number of patients transferred between pairs of hospitals. This variable is included in the model to capture the strength of a tie. This variable measures how many patients have been transferred between sender and receiver hospitals at time t.

Tie strength 2. Tie strength is raised to the power of 2 to take into consideration the non-linearity in Hypothesis 1.c. This variable is included in the model to capture the direction and steepness of the curvature, i.e. a positive value shows the curvature is upwards while a negative

value shows the curvature is downwards. A positive effect of tie strength and a negative effect of tie strength squared will indicate a U-shaped relationship that is, as tie strength increases performance differentials will tend to increase first and then to decrease.

Direct tie. This variable reports the existence of a tie between pairs of hospitals. This is a binary variable where 0 is assigned to pairs of hospitals that are not connected to each other and 1 is assigned to pairs of hospitals that are connected. This variable is included in the model to capture the extent to which two hospitals are connected via patient transfer relations.

Network subgroups. This variable is measured as clique co-membership. It describes the number of cliques in which members of an organisational dyad meet each other. Cliques are defined as maximally complete sub-sets of groups with three or more members (Wasserman and Faust, 1994). In the inter-hospital patient transfer network, there are cliques with a significant degree of overlap, the mean number of common clique is 0.53 (s.d. 3.34), and the maximum number of cliques in which two hospitals are jointly present is 101. Clique analysis was performed for each of the years 2006-2009 by using Ucinet version 6.187.

Network subgroups 2. Network subgroups is raised to the power of 2 to take into consideration the non-linearity in Hypothesis 2.b. This variable is included in the model to capture the direction and steepness of the curvature i.e. a positive value shows the curvature is upwards while a negative value shows the curvature is downwards. A positive effect of clique co-membership and a negative effect of clique co-membership squared will indicate a U-shaped relationship that is, as clique co-membership increases performance differentials will tend to increase first and then to decrease.

Network positions. This variable is measured as structural equivalence. This variable is calculated using the correlation of the rows and columns of the inter-organisational patient transfer networks, a well-known measure of similarity in the relational profiles of two structurally equivalent organisations (DiMaggio, 1986). The result is a matrix *S* of correlation coefficients in which the value of the cells (s_{ij}) varies between -1 and +1. The closer s_{ij} is to +1, the more *i* and *j* have similar relational profiles/ identical ties. Structural equivalence analysis was performed for each year 2006-2009 by using Ucinet version 6.187.

Network positions 2. Network positions is raised to the power of 2 to take into consideration the non-linearity in Hypothesis 3.b. This variable is included in the model to capture the direction and steepness of the curvature i.e. a positive value shows the curvature is upwards while a negative value shows the curvature is downwards. A positive effect of structural

equivalence and a negative effect of structural equivalence squared will indicate a U-shaped relationship that is, as structural equivalence increases performance differentials will tend to increase first and then to decrease.

The research design is at the dyadic level. The unit of observation is the dyad as the smallest possible level of analysis to detect peer effect. The four independent variables representing tie strength, direct ties, clique co-membership and structural equivalence are reported to a dyadic level in the following way. Tie strength: the extent to which the number of patients are transferred within each dyad. Direct tie: the extent to which organisations within each dyad are connected. Clique co-membership: the extent to which organisations within each dyad are members of the same (number of) cliques. Structural equivalence: the extent to which organisations within each dyad are similar in their structural position within the network. Furthermore, the two main variables of theoretical interest such as tie strength and direct ties (i.e. the intensity of relation and the existence of relation between pairs of hospitals) concern dyadic-effect and the other two main variables of theoretical interest such as network subgroups and network position concern extra-dyadic effect. These effects empirically capture different mechanisms and the four variables are weakly correlated to each other, as shown in the table 13. Table 14 reports the correlation among the squared network variables and shows that the three variables are weakly correlated to each other.

Table 13: Network variables and corresponding correlation

	Tie strenght	Structural equivalence	Clique co-membership	Direct tie
Tie strenght	1.0000			
Structural equivalence	0.0872	1.0000		
Clique co-membership	-0.0002	-0.0064	1.0000	
Direct tie	0.2978	0.2482	0.0060	1.0000

Table 14: Squared network variables and corresponding correlation

	Squared tie strength	Squared structural equivalence	Squared clique co-membership
Squared tie strength	1.0000		
Squared structural equivalence	0.0030	1.0000	
Squared clique co-membership	-0.0010	-0.0070	1.0000

4.3.3.1.2 Dependent Variable

Performance similarity. Performance similarity is measured using the Comparative Performance Index (CPI). The CPI captures the operational aspect of the supply of healthcare services, i.e. it takes into account the time and the ability of hospitals to successfully treat cases with similar complexity. Specifically, the CPI is a composite index that calculates the effectiveness – in terms of length of stay – of a hospital relative to the average effectiveness of a reference set of hospitals at regional level with an analogous composition of cases treated that are categorized into diagnosis related groups (DRGs). The CPI is calculated as:

$$CPI = \frac{\sum_i d_i N_i}{\sum_i D_i N_i}$$

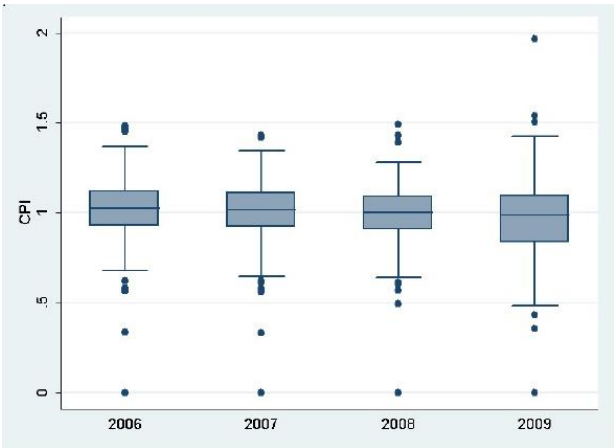
where d_i is the average length of stay (ALOS) in hospital *i* (weighted by the average Case Mix of hospital *i* as defined below), D_i is the average length of stay in all the hospitals in the Region (weighted by the average Case Mix of hospitals in the Region), and N_i is the number of discharged patients in all hospitals in the Region summed across all diagnostic categories (Gianino *et al.*, 2006).

This variable is used in the Italian healthcare sector for a number of reasons: first, it is explicitly comparative. The CPI compares the effectiveness of hospital relative to that of a standard set of hospitals at the regional level. The index takes the value of 1 for hospitals whose

performance is average compared with other hospitals in the region. It is lower than 1 for hospitals whose performance is above the regional average; and it is higher than 1 for hospital whose performance is below the regional average (Gianino *et al.*, 2006). Second, it is publicly available and hospital administrators can use it to understand which other hospitals perform similarly. Third, it is objectively measured by the Italian healthcare sector in the same way across hospitals.

A graphical representation of the CPI for all the hospitals in the Region from 2006 to 2009 is provided in the Figure 18, it shows the central tendency of the hospitals to be effective as reference hospitals in the region.

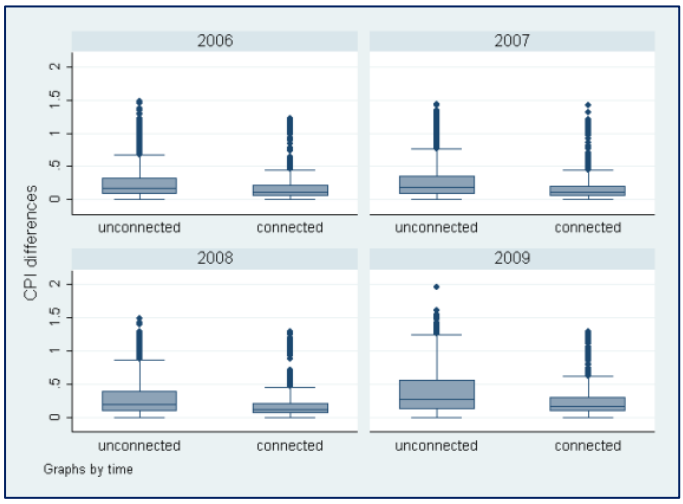
Figure 18: CPI, and corresponding effectiveness of the hospitals by time.



As I mentioned above, the CPI is used to measure performance similarity. More precisely, I compute the difference between any pair of hospitals in their CPI values. The absolute difference will create four matrices where the elements are the positive differences between the attribute scores of each pair of hospitals (Borgatti, Everett, & Johnson, 2018:98). The mean of the CPI differences is 0.27 (s.d. 0.29). This variable was created by using Ucinet version 6.187. The use of the difference between pair of hospitals allows me to detect specific direction of the assimilation effect and to ascertain if differences in performance are closed "from above" or "from below". In the former case, the differences decreases because the hospital with a higher level of performance decreases it as it relates to less efficient partners. In the latter case, the difference decreases because "partner with a lower level increases its performance.

The figure 19 shows that differences in CPI are smaller thus indicating performance similarity is less dispersed for connected dyads compared to non-connected hospital dyads. Indeed, differences in CPI are more dispersed and higher for non-connected dyads especially in 2008 and 2009.

Figure 19: Trend of CPI differences for connected and non-connected dyads by time



Performance similarity is included in the model as lagged variable in order to capture the effect of time dependency. Differences in performance at each time period may depend on differences in performance in previous time periods.

4.3.3.1.3 Control Variables

I controlled for a number of hospital-related characteristics that might affect the relationship between network-related properties and performance similarities among hospital organisations. These variables fall into two main categories: dyadic and monadic variables.

Dyadic covariates

Competitive Interdependence. This variable measures the level of competition between any pair of hospitals in the sample. The level of competition is computed by measuring overlaps in patient pools as suggested by Sohn (2002). This variable is included in the model to control how dependency on common resources (i.e. patients) influence performances similarity between sender and receiver hospitals.

Complementarity. This variable considers the set of organisational activities (specialties in my case) that hospitals hold. It is measured as Euclidean distance on the hospitals (n) by (m) specialties matrix. This variable is included in the model to control similarities (or differences)

in the set of specialties that hospitals offer. This variable captures the extent to which two hospitals that are similar in terms of services they offer are more likely to perform similarly.

Geographical proximity. This variable is the physical distance between each pair of hospitals. It is measured as distance in kilometres. This variable is included in the model to capture the effect of costs and risks associated with distance, and how this affects gaps in performance between pair of hospitals.

Disconnected hospitals. This is a binary variable where 0 is assigned to pairs of hospitals that are connected to other hospitals – and 1 is assigned to pairs of hospitals that are disconnected to other hospitals. This variable is used to control the extent to which two hospitals that are disconnected are more likely to perform differently.

Monadic Covariates

The second category includes organisation specific variables, or attributes.

Number of staffed beds. This variable measures the size of hospitals in terms of total number of staffed beds. This variable is included in the model to control for the extent to which two hospitals with a similar (different) size are more likely to perform similarly (differently).

Number of discharges. This variable measures the throughput aspect of a hospital's dimension in terms of total number of discharged patients. This variable is included in the model to control for the extent to which two hospitals with similar (different) number of discharged patients are more likely to perform similarly (differently).

Surgical Diagnosis related Groups (DRGs). This variable measures the complexity of cases in terms of percentage of surgical DRGs over the total DRGs. This variable is used to indicate patients with medical conditions that make their cases more complicated than those of the typical patient, hence those patients are not accounted for by patients'DRG classification (Bellavia *et al.*, 2012). This variable is included in the model to capture the extent to which two hospitals handling similarly complex cases are more likely to perform similarly.

Institutional category. This variable considers the institutional diversity of hospitals in terms of their ownership-governance. It is a categorical variable range from 1 to 6 (1= Hospital trust; 2= LHU hospital; 3= University hospital; 4=National institute for scientific research; 5= Classified hospital; 6 = Private accredited hospital).This variable is included in the model to

control for the extent to which two hospitals belonging to the same institutional category are more likely to perform similarly.

LHU membership. This variable indicates the membership to a specific Local Health Units (LHUs) in which the region is partitioned. This is a categorical variable range from 1 to 12 (1=RmA; 2= RmB; 3=RmC; 4= RmD; 5=RmE; 6= RmF; 7= RmG; 8=RmH; 9=Viterbo; 10=Rieti; 11=Latina; 12=Frosinone).This variable is included in the model to control for the extent to which two hospitals being membership of the same LHUs are more likely to perform similarly.

Level of care. This is a binary variable where 0 is assigned to pairs of hospitals that do not provide the same type of assistance – i.e. secondary and tertiary care- and 1 is assigned to pairs of hospitals providing the same type of assistance. This variable is included in the model to control for the extent to which two hospitals providing the same type of assistance are more likely to perform similarly.

Urban vs non Urban (receiver effect). This is a binary variable where 0 is assigned to pairs of hospitals that are located outside the metropolitan area and 1 is assigned to pair of hospitals that are located in the metropolitan area. This variable is included in the model to capture the extent to which hospitals that receive patients in the metropolitan area are more likely to perform similarly.

All the continuous, monadic variables are entered the model as absolute differences. All the binary and categorical variables entered the models as exact matches.

Table 15 reports the descriptive statistics and definition of all variables included in the empirical model specification.

Table 15: Variables included in our empirical model specifications: definitions and descriptive statistics; n=45828

VARIABLE	DEFINITION	TYPE	CONSTRUCT	DESCRIPTIVES			
				Mean	St.Dev	Min	Max
Dependent variable							
Comparative performance index	CPI measures the ability of hospitals to treat fast cases of similar complexity	Real	Performance	0.27	0.29	0	1.96

Main independent variables							
Tie strength (*dyadic*)	Number of patients transferred between hospitals	Integer	Strength of tie	1.44	10.10	0	774
Direct tie *(dyadic)*	Binary variable taking the value of 1 if there is at least one exchange from hospital i to hospital j, zero otherwise	Binary	Direct interaction	0.18	0.38	0	1
Clique co-membership (*dyadic*)	Number of cliques in which pair of hospitals are jointly members	Integer	Network subgroups	0.53	3.34	0	101
Structural equivalence (*dyadic*)	Correlation of the rows and columns of the inter-hospital patient transfers network	Real	Network positions	0.07	0.13	-0.072	1.00
Control variables							
Lagged Comparative Performance Index	CPI measures the ability of hospitals to treat fast cases of similar complexity at t-1	Real	Performance	0.25	0.27	0	1.49
N. beds (*monadic*)	Total number of staffed beds	Integer	Size	224.18	312.81	0	1903
N. discharges (*monadic*)	Total number of discharges	Integer	throughput	12534.67	20404.9	0	122657
Complex DRG (*monadic*)	Surgical DRGs over the total amount of DRGs (in percentage)	Real	Complexity	0.32	0.23	0	1
Level of care (*monadic*)	Dummy variable taking the value of 1 if a hospital provides specialized consultative care (i.e., tertiary care services), and zero otherwise (i.e., secondary care).	Binary	Type of assistance	0.77	0.41	0	1
LHU membership (*monadic*)	Categorical variable uniquely assigning each hospital to its reference LHU	Categorical	LHU membership	0.09	0.28	1	12
Organisational form (*monadic*)	Categorical variable uniquely assigning hospitals to institutional categories	Categorical	Institutional category	0.33	0.47	1	6
Competitive interdependence (*dyadic*)	Patient pool overlaps between every pair of hospitals as measured by Sohn (2002)	Real	Dependencies on (common) resources	0.11	0.17	0	0.81

Urban VS non Urban *(receiver effect)*	Binary variable taking the value of 1 if a hospital is located in Rome, and 0 otherwise	Binary	Metropolitan Area	0.50	0.49	0	1
Geographical distance (*dyadic*)	Distance (in kilometers) between every pair of hospitals	Real	Geographical proximity	50.26	40.20	0	222.59
Both disconnected *(dyadic)*	Binary variable taking the value of 0 if there is not connections at all to any other hospitals, and 1 otherwise	Binary	Isolated	0.001	0.01	0	1
Complementarity *(dyadic)*	Complementarity in the range of services measured as Euclidean distance on the hospitals (n) by (m) specialties matrix	Real	Service complementarity	3.22	1.07	0	6.24

4.4 Empirical Model Specification

I used a dyadic panel model. The dataset is dyadic because each observation refers to hospital dyads. For example, the dependent variable is dyadic as it measures similarity in performance. This dataset is panel because covers a 4-years period. The first lag of the dependent variable makes the model dynamic. Because the dependent variable is continuous, I use a multilevel regression estimated by Generalized Methods of Moments –GMM- (Arellano and Bover, 1995) and clustered the standard errors at the sender and receiver levels. The empirical model adopted in this study takes the following form:

$$E(Y_{ij,t}) = (\alpha Y_{ij,t-1} + \beta_1 I_{ij,t} + \beta_2 I^2_{ij,t} + \beta_3 C_{ij,t} + \beta_4 G_{ij,t} + \beta_5 G^2_{ij,t} + \beta_6 P_{ij,t} + \beta_6 P^2_{ij,t} + \beta_6 P^2_{ij,t} C_{ij,t} + \delta X_{ij,t})$$

where $Y_{ij,t}$ is the difference in performance between hospital i and hospital j at time t; $Y_{ij,t-1}$ is the one period lagged dependent variable; $I_{ij,t}$ is the strength of ties; $\beta_2 I^2_{ij,t}$ is the strength of ties raised to the power of 2; $C_{ij,t}$ indicates direct relations between hospital i to hospital j; $G_{ij,t}$ is clique co-membership; $\beta_5 G^2_{ij,t}$ is the clique co-membership raised to the power of 2; $P_{ij,t}$ indicates the degree of positional similarity; $\beta_6 P^2_{ij,it}$ is the positional similarity raised to the power of 2; $\beta_6 P^2_{ij,t} C_{ij,t}$ is the interaction effects for direct relation and structural equivalence; $X_{ij,t}$ summarizes the effect of covariates in the model, which may refer to i, j or both. Regarding parameters α is the effect of the lagged dependent variable, capturing persistence in performance similarity; the β measure the strength of the variables of theoretical interest; and

δ measures the effects of control variables. Because the data are dyadic, continuous organisational covariates, (i.e. num. of staffed bed) enter into the model as absolute difference in values that the covariate takes. The smaller the difference is, the more similar the hospitals are with respect to the considered variable. For covariates taking categorical (LHU membership) and binary values, an exact match is used to identify hospitals in the same category.

In this section, General Methods of Moment - GMM - approach is briefly introduced and its usefulness for the analysis of the data in this work is discussed as well as its limitations.

4.4.1 General Methods of Moments Estimation for panel dynamic data

The use of panel data to estimate dynamic econometric models has become popular among empirical studies (Maddala and Wu, 1999; Barro and Lee, 2013). The advantages of using panel dynamic data include: 1) the possibility to exploit the information present in the data, in terms of providing information about the relationship understudy at earlier time periods; 2) to specify any unobserved sources of heterogeneity across the unit of analysis i.e. organisations; and 3) to allow for more variation in the data in computing estimators. A typical situation with panel dataset is when there are larger number of cross-sectional units and only few time periods, hence a general estimation method that better suits with this situation is the General Methods Of Moments (GMM) (Greene, 2003; Bond & Windmeijer, 2002). The General Methods of Moments (GMM) is commonly used for this type of dynamic panel data model and allowing avoidance of unwanted assumptions, for instance to specify a particular distribution for the errors (Arellano and Honoré, 2001). It also permits to treat any unobserved individual heterogeneity correlated with the independent variable and the presence of heteroscedasticity with individual units' errors (Bond and Windmeijer, 2002). In GMM, assumptions that are referred to as moment conditions are made about the moments of the random variables as opposed to the assumptions of the entire distribution and hence can be considered to be robust. The moment conditions are allowed to be greater than the parameter numbers and this way GMM generalises the Method of Moments (MM). Sample averages and expected values are used to build the GMM where the model parameters use moment conditions that represent expected values in terms of the true moments. The moment conditions are modelled using the sample moment conditions and GMM estimates parameter values that are closest to the sample moment conditions given (Greene, 2003).

An important property of the GMM is the use of instrument variables[4] that are "internal" in the non- linear equation i.e. based on laggedness of the instrumented variables. As Arellano & Bond, (1991) point out the GMM permits to resolve the problem, where the model is defined in terms of a system of equations, one per period, and where the instruments are applicable to each different equation. The estimator is available in Stata as *xtbonds* allowing for the specification of the particular lag variables to be included in the model. Unlike alternative models such as panel data models, that do not include the lagged dependent variable, this approach permits to distinguish between state dependence and unobserved heterogeneity, that is in my paper, between cases in which hospitals i and j attaint the same levels of performance today because they have already collaborated in the recent past and, in turn, have influenced each other.

4.4.1.2 Estimation strategy for network data

The estimation of model requires addressing the methodological challenges posed by the dyadic structure of the network data. It is worth recalling that for the network data, the observations are dependent because each entity in the network matrix appears in multiple dyads, this leads to complex dependencies across observations (Stuart, 1998). Because of dependency, the coefficient estimates will be consistent, but the standard errors may be incorrect due to the dependency of the data. One way to overcome this problem is by introducing a fixed effect for each row or column in the network matrix, by clustering the standard errors on one dimension, and by applying the Hubert-White correction for heteroscedasticity, as several empirical studies have demonstrated. This is the traditional approach taken by many empirical studies (White, 1980; Powell *et al.*, 2005; Mascia, Pallotti and Angeli, 2017). This paper, however, focuses on another very popular approach, common in the econometrics studies, named two-way clustering. The two-way clustering allows for clustering the standard errors in two or more dimensions and works similar to the one-way approach. The two-way approach generates three different cluster-robust variance matrices such as the first dimension i.e. group 1; second dimension i.e. group 2; and third dimension i.e. group 1 by group 2. Then it creates a new dimension that accounts for double- counting, i.e. group 1 and group 2 and subtract the third dimension i.e. group 1 by group 2 (Cameron, Gelbach and Miller, 2011). The advantage to use this approach are, firstly the standard errors

[4] Instrumental variables are used when variables are endogenous i.e. variables that are correlated or influenced by other variables. It permits to identify unobserved correlation between independent and dependent variables.

are not repeated for one coefficient clustering in one way and for the second coefficient clustering in the second way; and secondly it allows to create a time variable (Cameron and Miller, 2015). This study uses the two-way cluster approach to address a major concern with dyad-oriented schemes and as shown by Lindgren (2010), this approach is suitable for network data because it better performs to handle network dependencies under the condition of heteroscedasticity; and its logic could be translated to social network data. In particular, he argues that 'the two-way clustering approach has a number of attractive features that may make this approach a suitable alternative when studying various types of social network analysis. Most importantly, by applying the two-clustering estimator we should be able to obtain correct standard errors even in the presence of both structural autocorrelation and heteroscedasticity of unknown form' (Lindgren, 2010:283). Accordingly, I adopt the same analytical strategy by introducing a GMM as estimator, by clustering the standard errors in two different non–nested dimensions, i.e. sender and receiver, by creating a time variable and correcting for heteroscedasticity. This strategy also allows controlling for any unobserved sources of heterogeneity across hospitals.

4.5 Analysis

4.5.1 Results

Table 16 reports the GMM estimates of a sequence of increasingly complete models, along the lines described in the previous section. Model 0 includes only the dependent variable and the control variables. Model 1 adds the effects of the dyadic relations in terms of direct relationships and their strength. Model 2 introduces the effect of clique co-membership. Model 3 adds the structural equivalence variable. Model 4 reports the full model, including the quadratic term of the main independent variables and their structural equivalence and the interaction term between a direct relationship and a structural equivalence. Because the dependent variable is measured as the difference in performance, a positive (negative) parameter suggests a larger (smaller) difference in performance, or, in other words, less (more) similarity. The discussion of the results with respect to the full model (Model 4) is summarised in Table 16.

Hypothesis Testing

Main effects

Overall, the results supported the research hypotheses. With respect to the hypotheses that examined the peer effects on the performance similarity at the dyadic level, Model 4 showed that the effect of a 'direct tie' (Hypothesis 1.a) was negative and significant, suggesting that two hospitals that connected with each other via patient transfer relations were more likely to perform similarly over time. The significantly negative parameter for 'tie strength' (Hypothesis 1.b) suggested that two hospitals that exchanged more patients were more likely to perform similarly over time. In other words, the number and the frequency of bilateral exchanges reduced the gap in performance between the sender and the receiver hospitals. The significantly positive parameter of the quadratic effect of 'tie strength' (squared tie strength) in Model 4 suggested that when the tie strength increased beyond a certain threshold, the effect of over-embeddedness dominated and made performance similarity less likely. Taken together, these two effects supported Hypothesis 1.c by suggesting a U-shaped relationship between the tie strength and the performance similarity. Concerning the hypotheses that examined the peer effects on the performance similarity in network subgroups, Model 4 showed that a 'clique co-membership' had no effect on performance similarity. I found no support for Hypotheses 2.a and 2.b.

Concerning the hypotheses that examined the peer effects on the performance similarity at the network level, Model 4 showed that the effect of 'structural equivalence' (Hypothesis 3.a) was negative and significant, suggesting that two hospitals that occupied the same network position were more likely to perform similarly over time. The significantly positive parameter of the quadratic effect of 'structural equivalence' (squared structural equivalence) suggested that when the structural equivalence increased beyond a certain threshold, the effect of competition prevailed and made the performance similarity less likely. Taken together, these two effects confirmed Hypothesis 3.b by suggesting a U-shaped relationship between the structural equivalence and the performance similarity.

Table 16: Multiple regression results estimated by GMM

Variable	Model 0	Model 1	Model 2	Model 3	Model 4
Lagged CPI (diff.)	.81110064***	.80458309***	.80439828***	.79693618***	.79149801***
Tie strength		-.00012043	-.00012103	-.00010518	-.00048492**
Direct tie		-.04520273***	-.04524559***	-.03858156***	-.0447823***
Clique co-membership (network subgroups)			-.00048676	-.00052646	-.00113183
Structural equivalence (network positions)				-.14817162***	-.35200682***

Squared tie strength					1.726e-06*
Squared clique co-membership (network subgroups)					.00001455
Squared structural equivalence (network positions)					.3253148***
Interaction effect Direct tie*Structural equivalence					.08845321***
Geographical distance	-.00043122***	-.00050836***	-.00050865***	-.00061213***	-.00068475***
Competitive interdependence	-.14463582***	-.14174899***	-.14188843***	-.13968556***	-.13532698***
Service Complementarity	-.01461249***	-.01094972***	-.01090509***	-.00967657***	-.00776553***
Number of beds (diff.)	.00008502***	.00009324***	.00009317***	.00008839***	.00008742***
Number of discharges (diff.)	-6.751e-07***	-7.629e-07***	-7.643e-07***	-7.946e-07***	-8.058e-07***
Surgical DRG (diff.)	.03441298***	.02749632***	.02752238***	.02341608***	.02078299***
LHU (matches)	-.0094513*	-.00121273	-.00121091	-.01421903***	-.00927625*
Organisational form (matches)	.01090733***	.01203994***	.01203527***	.01594943***	.01641053***
Metropolitan location (receiver effects)	-.0006506	-.0006089	-.00060202	-.00082102	-.00095147
Level of care (matches)	.00625379*	00559209	.00515895	.00464946	.00460906
Both disconnected (matches)	-.11401722*	-.11277599*	-.11287915*	-.11935851*	-.12234309*
Cons	.12789819***	.13078182***	.13133828***	.14392827***	.15007947***
Hansen test of overid. restrictions					*3.24 Prob > chi2 = 0.356*
Hansen test excluding group (test of exogeneity of instrument subsets)					*chi2(1) = 0.24 Prob > chi2 = 0.625*

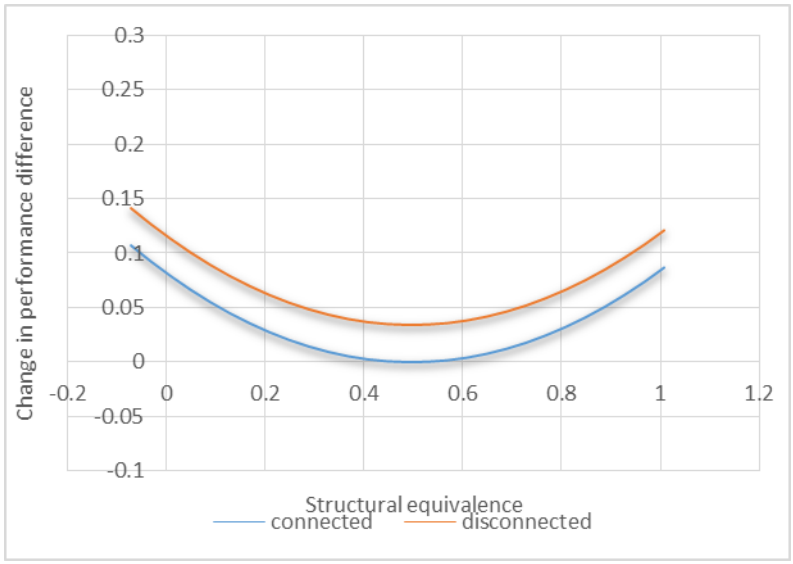
Legend: * p<0.05; ** p<0.01; *** p<0.001

Interaction effects

In Hypothesis 4, I examined the interaction effect of direct relationships and structural equivalence on performance similarity. The interaction term captured the idea that being connected and occupying similar network positions led to a more similar performance. I found support for this Hypothesis, suggesting that the more strongly connected and structurally equivalent two organisations are, the more similar is their performance, as compared to other organisations that do not have the same network-related characteristics. To interpret the results more intuitively, performance similarity (or differentials) and structural equivalence were

plotted for connected and disconnected hospital organisations (Fig. 20). Figure 20 shows how the performance differentials for connected and disconnected organisations varied as the structural equivalence varied with an increment of 0.04. The U-shaped curves showed that for the high and the low levels of structural equivalence, the difference in performance for the disconnected and structurally equivalent organisations was higher than that for connected hospital organisations.

Figure 20: Effect of structural equivalence on performance differentials



Control variables

Model 4 also showed the effects of the control variables. Hospitals of similar size (positive number of beds), handling similar complex cases (positive surgical diagnosis-related groups), having different institutional ownerships (positive organisational form), and sharing different LHU memberships (weakly positive LHU membership) were less likely to perform similarly. Hospitals that were located close to each other (negative geographical distance) and were disconnected (weakly negative both disconnected) were more likely to perform similarly. The effect of competitive interdependence was negative and significant, suggesting that two hospitals that depended on common resources (patients) were more likely to have similar performance. The effect of service complementarity was negative and significant, suggesting that two hospitals that were similar in terms of the services that they offered were more likely to perform similarly. Finally, the effect of the number of discharged patients was negative and significant (negative number of discharges), suggesting that two hospitals having a similar number of discharged patients were more likely to perform similarly. The predicted effects of

various network levels on the performance similarity remained unchanged after controlling for the control covariates.

4.5.2 Robustness Check

The results discussed above (reported in Table 6) were obtained by estimating a generalised method of moments with robust standard errors and using the specifications listed in Section 4. For the sake of comparison, I also considered the linear equation (M3), its restricted version (M0), and the equation including the quadratic term (M4) of the independent variables as suggested by Pallotti et al., (2015). The results of the statistical test (Wald's test) for the empty, linear, and quadratic models showed that the statistical test rejected the null hypothesis and that the linear network variables were a statistically significant improvement in the fit of the model as compared to the empty model. Second, I repeated the analysis by using the cross-sectional and panel versions of the data, where the results and interpretations were entirely consistent with those presented above: the peer effects were stronger when two organisations were connected and structurally equivalent (see the Appendix A).

4.6 Discussion and Conclusion

An important insight produced by the studies on peer effects is that when peer effects operate through network relationships, such effects are not homogenous and depend on the positions that the social actors occupy within the network (Patacchini et al., 2017; Calvó-Armengol et al., 2009). Another important insight produced by the studies on IONs is that organisational behaviours and performance are affected by the patterns of connectivity and position similarity within the network. By becoming relationally and positionally embedded in IONs, peer effects operate simultaneously at different network levels and lead the organisations to behave similarly (Pallotti et al., 2015; Mizruchi & Marquis, 2006).

The current work took both these intuitions as a starting point and was based on the claim that if peer effects are seen as the association between the outcomes of social actors that interact with each other (Bramoullé, Djebbari and Fortin, 2009), then the establishment of collaborative relationships among the organisations leads these organisations to perform similarly over time. The results obtained in this study contribute to this stream of research by examining the range of peer effects that propagate beyond the dyadic relations, through the network subgroups and

positions in the network as a whole. In contrast to studies examining peer effects at one level of analysis, this study accounted for the inter-relationship of multiple network levels in explaining the inter-organisational performance similarity between the connected organisations. The motivation behind the idea of comparing the different network levels was to understand which different mechanisms were at work. Specifically, the current study focuses on similarity in performance providing information about the assimilation mechanisms between two organisations if there were influence. But the existence of peer effects brings differentiated social mechanisms to the members of the inter-organisational peer networks depending on: (i) strength of relationship with a direct network partners; (ii) share in membership in the network subgroups; (iii) and network positions in the network as a whole. These three levels correspond to specific assimilation processes involving from local to larger sub-sets of network. Therefore, it could be possible to associate the dyadic level (first level) with the mechanism involving social learning as an intense exchange of information transferred through the relationships with the immediate partners (Beckman and Haunschild, 2002). The network subgroups (second level) was associated with the mechanism involving social conformity as a cohesive relationship within the subgroups, exposing the members to more pressure (Rowley *et al.*, 2005). Finally, network position (the third level) was associated with the mechanism involving competition, as structurally equivalent organisations depend on common resources controlled by the same third parties (Mizruchi,1993; Burt, 1987). All of these mechanisms generated by the existence of peer effects could explain how and why organisations perform similarly. The added complexity stemmed from the importance of using different network levels to predict the similarity in performance in the empirical context by using the longitudinal data of the patient transfer relations between hospital organisations.

The results showed that the peer effects operated more strongly at the dyadic and network levels. More specifically, I found that both direct ties and their strength were significantly associated with the performance similarity between the two hospitals. These results were in line with the existing literature that emphasises that organisations 'would look to their peers with whom they shared social ties and would be influenced by their behaviour' (Mizruchi & Marquis, 2006:4). I also found that the tie strength has a non-linear effect on performance similarity: as the intensity of direct relationships increases, the organisational performance similarity increases at first and then reaches a maximum point beyond which the further increases in the intensity of ties are accompanied by a decrease in the performance similarity. This is the case because a greater volume of exchanges and frequent exchanges enable

organisations to trust their peers and to share more information, consequently shaping their behaviours accordingly. In their study of the diffusion of innovation and learning within healthcare organisations, Goes & Park (1997) showed that a greater volume of exchanges between hospitals is more likely to increase the level of innovation between hospitals whereby more frequent interactions lead to a greater sharing of information and technical practices among the hospitals. However, bilateral exchanges that include highly embedded relationships are particularly prone to be excluded from the network (Uzzi, 1996).

In contrast to the past research on peer effects on network subgroups (Tim J Rowley, Baum, Shipilov, Greve, & Rao, 2004; Hedström, Sandell, & Stern, 2000), where the clique co-membership was significantly associated with the inter-organisational performance similarity (Pallotti, Tubaro and Lomi, 2015), this study could not find evidence for the following: organisations that share the same cliques have no effect on performance over time, all other things equal. A possible explanation for this is related to the over-embeddedness argument (Uzzi, 1997), where a greater embeddedness of organisations in a clique 'leaves organisations with a lower capacity of absorbing new ideas' (Zuckerman & Sgourev, 2006:37) and hence, the similarity starts to decline. In this study, I measured the peer effects on the network subgroup by using the clique co-membership; however, different conceptions have been theoretically and empirically developed in the literature (Rowley, Greve, Rao, Baum, & Shipilov, 2005; Hedström, Sandell, & Stern, 2000). Future research could use alternative measurements of this concept to understand how peer effects operate at the network subgroup level.

Finally, I found that peer effects operated more strongly at the network level. Perhaps, the most revealing result of my study concerns, indeed, the role of structural equivalence as an indicator of the source of influence and hence of predicting the behavioural similarity (e.g. performance). In particular, I found a linear effect of structural equivalence on the performance similarity, suggesting that the performance similarity increases with an increasing similarity in the position dependence patterns over time. This result agrees with the literature that suggests structural equivalence as the main source of variation in constraints and opportunities and thus, similar behaviour (Pallotti et al., 2015; Mizruchi & Marquis, 2006; R. Burt, 1992). In contrast, I found a non-linear effect of structural equivalence on performance similarity: as the positional similarity relationships increased, the organisational performance similarity increased at first and then reached a maximum point beyond which any further increases in the positional similarity were accompanied with a decrease in the performance similarity. This was attributed

to the fact that occupying the same network positions exposed the organisations to the same sets of constraints and opportunities (i.e. higher level of competition), whereby structurally equivalent organisations used one another to gauge their strategies in a way that they differed in terms of the strategy adopted (or they adopted the same strategy) from their peers or competitors (Burt, 1987). In a more speculative mode, the concept of structural equivalence suggests that organisations that are structurally equivalent may represent similar social roles: two organisations are similar if they fall into the same *equivalence class*, meaning that they play the same roles in the network and are involved in similar types of relationships (Mizruchi, 1993; Lorrain & White, 1971). As Burt noted 'the more similar ego's and alter's relations with other persons are – that is, the more that alter could substitute for ego in ego's role relations, and so the more intense that ego's feelings of competition- the more likely it is that ego will quickly adopt any innovation perceived to make alter more attractive as the object or source of relations' (Burt, 1987:1291). Compared with hospital organisations, teaching hospitals are more likely to be guided by the same practices and technical procedures, whereby the influence takes place among those similarly positioned in the network of collaborative relationships. Finally, I found support for the interaction effect between structural equivalence and a direct relation, suggesting that two organisations that were connected to each other through some patients exchange and occupied similar network positions displayed a more similar performance.

My study provides evidence for the idea that the way in which organisations change their behaviours is contingent on how organisations are embedded in the network of collaborative relationships. In more general terms, the results reported here lend credibility to the view that peer effects involve the consideration of different network levels, i.e. from dyadic to global network systems. This work builds on the previous research on peer effects and on inter-organisational literature, and I have extended the continuing debate over the level at which the peer effects operate (Pallotti et al., 2015; Mizruchi & Marquis, 2006). The results provide an insight into which level is more appropriate for understanding the similarities in performance between organisations over time.

4.6.1 Limitations and future research directions

As with all research, this study has two important limitations. The first limitation is specific to my research design. Peer effects are detected by looking at the association between organisational outcomes (Bramoullé, Djebbari and Fortin, 2009) by using a continous variable:

organisational performance,(i.e CPI) as a dependent variable and by using network measures as indipendent variables (i.e. tie strengh, network subgroups, and network position). GMM is appropriate because of the continous nature of the dependent variable (i.e. performance). The traditional social influence model in SAOMs[5] work for categorical variables only. Furthemore SAOMs is a model for behaviour change, for instance, smoking after befriending people who smoke. In this current study, the limitation is more specific to my study and concers the fact that my research design produced no information about a particular behaviour that defined exactly what hospitals changed as a results of their partecipation in the network. Ideally, I would have liked to collect information on collaboration between doctors via co-involment on the same clinical case within the same hospital (clinical practice) or on how hospitals handle the administration through sharing electronic health information exchange. In both cases require access to clinical records at every hospitals and these data are not cointained in my information sources. My data produces information about the indirect consequence of a behaviour (i.e., similarity in interorganizational performance) and consequenlty I assumed implicitly that some undefined behaviour change brought about a change in performance. SAOMs would have required much more precise information about hospital's behaviour to applied consistenlty. While GMM is more flexible in that and it enables to detect the association between network and some indirect consequence of behaviours, whitout much detail about these behaviours. Also, I followed the approach suggested by Mizruchi & Marquis (2006) and Pallotti, Tubaro and Lomi (2015). Future studies that will not discover the existence of peer effects by using a continuous variable, i.e. organisational performance as dependent variable as this study did, will be able to overcome this limitation by incorporating network variables that capture directly the evolution of network attached to organisational behaviour and the mediating mechanisms. Moreover, dyadic network data are characterized by complex dependencies across observations and this statistical model only controls for such dependencies without modelling them. Future studies can use statistical advanced network that allows to control and model the local dependencies by specifying hypotheses about the endogenous network process (Burk et al., 2007).

The second limitation is the context of the study needs to be considered. Hospitals can be considered only as one sample of organisations with strong institutional factors. Nevertheless,

[5] Only recently new developments have been proposed that extend the influence model to continuous behavioural variables (Niezink & al., 2019). With this new extension, it will be possible to test similar predictions on how the network structure affects (individual or organisational) behaviours.

determining how peer effects operate at different network levels is a point that could be generalized in different settings that overcoming the specific institutional factors examined here. Comparative analysis could provide further insights on why and at which network levels hospitals tend to perform similarly. Future research could use the statistical model that this research proposed to draw a comparative analysis in different institutional contexts.

Despite the obliviously limited scope conditions that these qualifications impose, the findings in this paper remain useful as they create a bridge between economics literature peer effects and network literature: the role of different network levels. My study was motivated by one basic question: at what levels are peer effects more likely to operate? My results provide an answer for understanding similarities in behaviour among organisations.

Chapter 5: Geographical proximity and social similarity in Inter-organisational networks: A longitudinal study

Abstract

According to the literature on inter-organisational networks, geographical proximity is one of the most important factors explaining the formation of exchange relations among organisations. This is because the risks and costs associated with resource transfers make collaboration more likely to occur between geographically proximate organisations. However, empirical research suggests that other forms of proximity may be important drivers of the network tie formation. This paper focuses on social similarity. Building on the theoretical distinction between the physical and the social space, in this study, I test the conjecture that the effect of geographical proximity (i.e. distance in the physical space) on the formation of collaborative network ties among organisations is moderated by the effect of social similarity (i.e. distance in the positions that organisations occupy in a relational space). In particular, I seek evidence of a decreasing negative effect of geographical distance when the social similarity increases.

To test this hypothesis, this paper used longitudinal data on patient transfers collected within a regional community of hospital organisations over a period of four years. The number of patient transfers is used to measure the intensity of inter-hospital collaboration. The distance in kilometres is used as a measure of geographical proximity among the hospitals in the sample. Finally, structural equivalence is used to measure the social similarity. Analytically, I used the dyadic panel data and Poisson regression with exponential feedback estimated by the generalised method of moments (GMM), to model the inter-organisational collaboration as a function of geographical proximity, social similarity, and a number of organisational and institutional variables to control for additional factors affecting the inter-organisational collaboration. The results show that social similarity moderated the effect of geographical proximity in the expected directions: the negative effect of geographical distance decreased with an increase in the similarity of network positions. The main finding of this study is that the effect of geographical proximity is contingent on the positions that the organisations came to occupy within the relational space.

Keywords: inter-organisational collaboration networks, social similarity, structural equivalence, geographical proximity, longitudinal network data.

Highlights

- Exploring the relationship between geographical proximity, social similarity, and inter-organisational collaboration networks
- Identifying a measure of social similarity that is positional rather than relational
- The negative effect of geographical distance tends to decrease with an increase in the similarity of network positions
- Competitive pressures foster the creation of collaborative relations across a long distance

5.1 Introduction

There is growing recognition in the literature that geographical proximity (or its opposite, i.e. geographical distance) fosters the formation and endurance of inter-organisational exchange resources (Mascia, Pallotti, & Angeli, 2017; van Zelst, Mannak, & Oerlemans, 2017; Knoben & Oerlemans, 2012; Rivera, Soderstrom, & Uzzi, 2010; Knoben & Oerlemans, 2006). This is because in organisational landscapes, production and exchange activities are frequently concentrated in space (Krugman, 1991). Organisations are more likely to select geographically proximate exchange partners because co-location reduces the costs and the time associated with transfers, facilitates awareness about the potential partners (Rangan, 2000), and controls and coordinates the exchange of symbolic and material resources (Capaldo and Petruzzelli, 2014; Gnyawali and Park, 2011). For instance, Amati and colleagues (2019) found that hospitals are more likely to collaborate and share resources in a timely manner when they are located close to one another.

The relation between geographically proximity and networks has also attracted the attention of economic geographers (see Balland, Boschma, & Frenken, 2015 for a recent literature review). Interest in inter-organisational networks stems from their consideration as a social infrastructure that organisations build to manage their resource dependencies and coordinate production relations across corporate boundaries (Ter Wal and Boschma, 2009). Because production and exchange activities are concentrated in space (Krugman, 1991), and proximity facilitates the creation of network ties (Whittington, Owen-Smith and Powell, 2009), the effects of geographical proximity and network spaces must be considered jointly (Ter Wal and Boschma, 2009). From this perspective, organisations are likely to select partners who are close

to another in the physical and the non-physical space, i.e. network space (Hansen, 2015; Knoben & Oerlemans, 2006; Boschma, 2005). Therefore, other forms of non-physical proximity have been suggested by Boschma (2005) by distinguishing between geographical, cognitive, organisational, social, and institutional proximity (Hansen, 2015; Scherngell & Barber, 2011; Breschi & Lissoni, 2009).

Among the non-physical forms of proximity, social similarity (or its opposite, i.e. social distance) is the one that better captures the concept of social space (Hollway *et al.*, 2017). Social similarity can be associated with the presence of exchange relationships (Uzzi, 1996), between organisations and is typically measured as the strength of a tie, emphasising its relational dimension (Boschma, 2005). Empirical work shows that organisations that are embedded in a web of relationships are more likely to exchange resources with distant partners (Knoben and Oerlemans, 2012). This happens because strong social ties provide information about resources (Gulati, 1995) and generate trust in potential partners (Uzzi, 1996). Therefore, it has been argued that the formation of collaborative relationships depends on the pattern of relationships established among organisations (Beckman, Haunschild and Phillips, 2004), whereas geographical proximity (along other dimensions) may reduce the coordination costs and space for information. Consequently, social similarity also contributes to the formation of network ties among organisations (Brass, 2011; Reagans, 2011). However, social similarity has been operationalised in many different ways, showing larger amounts of overlap with the other non-physical forms of proximity (Knoben and Oerlemans, 2006).

The current study uses a measure of social similarity that goes beyond the dyadic level and focuses on the position that organisations occupy in a social/network space, emphasising its positional dimension. The aim of this study is to investigate how social similarity and geographical proximity interact with each other, while taking into account other forms of proximity. Some evidence for the dynamic interplay between social similarity and geographical proximity is available (Bergé, 2017; Ter Wal, 2013; Reagans, 2011; Sorenson & Stuart, 2008), but they considered social similarity at the dyadic level, i.e. strong interactions among social actors.

The main research question that this study attempted to answer is the following: *What is the joint effect of geographic proximity and social similarity on the formation of collaborative network ties among organisations?*

By answering this question, the current study contributes to the on-going debate on the dynamic interplay between geographical proximity and network dimensions by empirically exploring how the effect of geographic proximity is contingent on the positions that organisations came to occupy within social networks. In particular, this study contributes to and built on the existing research in two ways. First, by using a longitudinal design, this work shows how geographical proximity and social similarity influence the formation of network ties over time. Researchers have emphasised the importance of using a longitudinal framework to investigate the dynamics of inter-organisational collaboration and proximity (Broekel and Hartog, 2011; Ter Wal and Boschma, 2009).

Second, this study uses a measure of social similarity that is positional rather than relational (Boschma, 2005; Uzzi, 1996). The proposed measure uses the notion of structural equivalence to operationalise social similarity. In this study, I explore how the position of organisations in both physical and network spaces interacted to affect the patterns of collaboration among organisations. Moreover, the proposed measure focuses on the position of organisations in social networks as a whole, thus going beyond the dyadic measures that have been proposed in the literature (Knoben and Oerlemans, 2006).

The empirical case was developed around the longitudinal data of patient transfer relationships collected within a community of hospital organisations from 2006 to 2009. Previous studies have documented that patient transfers require high levels of coordination and interaction between partner hospitals (Lomi & Pallotti, 2012; Lee et al., 2011). Therefore, patient transfer relationships can be conceived as a form of inter-organisational collaboration (Kitts, Lomi, Mascia, Pallotti, & Quintane, 2017; Mascia et al., 2017; Mascia, Di Vincenzo, & Cicchetti, 2012).

The rest of this paper is organised as follows: In Section 5.2, the theoretical background of the antecedents of inter-organisational collaboration is presented, focusing on the role of network-based mechanisms and their interplay with geographical proximity. Section 5.3 describes the research design and research methodology used. Section 5.4 reports the empirical estimates. Section 5.5 concludes the paper by discussing the results and by outlining the potential directions for future research.

5.2 Theory and Hypotheses

In this section, I will discuss the determinants of inter-organisational collaboration among organisations. More specifically, the first subsection starts by explaining the micro-determinant of collaboration stemming focusing on the idea of network positions and its link with the notion of social similarity - or social proximity- (subsection 5.2.1). The next subsection will explain the role of geographical proximity on the formation of collaborative relations (5.2.2). The final subsection (5.2.3) will discuss the interplay between geographic proximity and social similarity.

5. 2.1 Social similarity and inter-organisational collaboration

Thus far, most of the research in this field has focused on social similarity as an antecedent of network tie formation among organisations (Reagans, 2011; M. Kilduff & Brass, 2010). The underlying idea is linked to the fact that similarity brings up connections among organisations in a relational space (Brass, 2011). Social similarity fosters trust and an exchange of resources (Oerlemans and Meeus, 2005) and hence, increases the probability of collaboration among organisations.

In traditional studies, social similarity emphasises the "conceptual ambiguity" of proximity theory (Knoben & Oerlemans, 2006:79). It refers to personal proximity (Schamp, Rentmeister and Lo, 2004) or relational proximity (Coenen, Moodysson and Asheim, 2004). Some researchers use this notion either as part of other forms of proximity, i.e. organisational proximity (Filippi and Torre, 2003) or as independent from other forms of proximity (Coenen, Moodysson and Asheim, 2004). Social similarity comes from the embeddedness theory emphasising that any economic exchanges are affected and integrated in a social context (Granovetter,1985). The social context is represented by social relations between social actors which impact on their economic behaviour and exchange (Boschma, 2005; Uzzi, 1996). Social similarity is defined "in terms of socially embedded relations between agents at the micro-level" (Boschma, 2005:66) and measured as strenght of ties (e.g. resulting from past collaboration). Traditionally, it has been operationalised at the dyadic level. For example, it has been measured by counting the number of past collaborations (Boschma, Balland, & de Vaan, 2014; Ahuja, Polidoro Jr, & Mitchell, 2009). Using patent data, Singh, (2005) measured social similarity by counting the number of past collaborations. He found a positive effect of social similarity on the propensity to collaborate, while controlling for geographical proximity. Using the data on R&D cooperation, Autant-Bernard, Mairesse, & Massard (2007) investigated different types of proximity and measured social similarity as the strength of social ties between

economic actors. They found that social proximity encourages the formation of inter-organisational collaboration.

Recently, empirical research has also considered the effect of indirect relations by measuring social similarity at the group level (i.e. meso level). For example, it has operationalised by considering whether economic actors belong to the same social group, such as cliques (Pallotti, Tubaro, & Lomi, 2015; Broekel & Hartog, 2011) or by considering network closure as an indicator of social similarity (Bergé, 2017; Ter Wal, 2013). Pallotti et al. (2015) considered the relational dimension of social proximity and used clique co-membership as an indicator of social proximity determined by the membership in overlapping cliques. They found a non-linear relationship between social similarity and the propensity to collaborate. Using data on European scientific co-publications, Bergé (2017) measured social similarity by counting the number of indirect ties between economic actors. He found that social similarity is an important factor that drives future collaborations, but its effects are mediated by geographical proximity. Using network closure as an indicator of social similarity while taking into account geographical proximity, Ter Wal (2013) found that indirectly connected organisations are more likely to form collaborative ties.

Overall, these empirical studies have illustrated two points: first, theoretically, social similarity makes visible that economic actions of organisation is influenced by their social relations, and therefore the importance of social relations. Second, empirically, social similarity has been operationalised at different levels.

Social similarity therefore reflects the importance of having a social relations which result in repeated and stable relationships (Boschma, 2005). Social relations are often accompanied by information/ knowledge sharing (Knoben & Oerlemans, 2006) which lead similar organisations to interact together in order to mobilise resources. This vision is strongly linked to the idea of structural equivalence or similarity in network positions that organisations come to occupy by virtue of similarity in their relationship patterns with other organisations (Lorrain and White, 1971). Two structural equivalent organisations that share the same relational profiles are more likley to interact more with each other (Burt, 1987) as the more similar organisations – in terms of their relational profiles- are, the more likely organisations will share routines and familiarity concerning the mutual economic exchange (Oerlemans and Meeus, 2005). On other hand, network positions also consider the overall network of relations in which economic action of organisations is embedded within the whole network (Mizruchi, 1993).

Consequently, social similarity positively influences network ties formation between organisations. Therefore, the first hypothesis is as follows:

Hypothesis 1: Social similarity is positively associated with the intensity of collaboration among organisations.

Some precision needs to be applied to the notion of social similarity that will be used throughout this paper. The notion of social similarity can be related to the notion of social proximity, emphasizing organisations with 'similar positional embeddedness profiles' (Pallotti et al., 2015:193). The hypothesis suggests that organisations are similar proximate with respect to their relational/ profiles, the higher will be the likelihood to create collaborative relationships.

In addition to the similarity in the relational space, geographical proximity provides opportunities to the development of collaboration between organisations. The next subsection discusses how geographical proximity affects the creation of future collaborations.

5.2.2 Geographical proximity and inter-organisational collaboration

The role of geographical proximity in the development of inter-organisational exchange resources is well-known in the literature (van Zelst et al., 2017; Knoben & Oerlemans, 2012; Baum & Mezias, 1992). Geographical proximity is defined as the 'spatial or physical distance between economic actors, both in its absolute and relative meaning' (Boschma, 2005:69). Three fundamental advantages are attached to the role of geographical proximity: first, geographical proximity encourages face-to-face interactions and increases the probability to meet potential partners (Bergé, 2017). Second, it reduces the cost and time of moving resources among the organisations' partners (Torre and Rallet, 2005). Third, co-location in the same cluster facilitates the access to complementary resources due to the presence of different partners (Neffke, Henning and Boschma, 2011). All of these advantages could be considered to be mechanisms that lead to the formation of collaboration between organisations. Therefore, organisations show preference for geographically proximate partners (Gulati and Gargiulo, 1999) or partners located in the same industry or region (Trapido, 2007). Indeed, geographical proximity makes collaboration more likely to occur among proximate partners, as they find it easier to access and share resources. This is aligned with the findings of Hansen (2014), who observes that organisations select proximate partners because it is simple to share symbolic and

material resources. Ponds, Van Oort, & Frenken (2007) investigated the role of geographical proximity in the formation of collaboration among university organisations and found that proximate organisations tend to select each other and hence to collaborate. Powell, White, Koput, & Owen-Smith (2005) observed that organisations choose their partners on the basis of their locations; more specifically, they found that organisations collaborate with geographically proximate partners. Mascia et al. (2017) investigated the role of geographical proximity between hospital organisations and found that hospitals are more likely to transfer resources, i.e. patients, across short distances and have a higher propensity to collaborate.

In addition, while being geographically proximate increases the possibility to collaborate, geographical distance is inversely proportional to the propensity of collaboration among organisations. Mascia et al. (2012) found that hospitals located in the same area are more likely to collaborate, while hospitals located at a greater distance from each other are less likely to collaborate. Pallotti, Lomi, & Mascia (2013) showed that hospitals that are closer to each other tend to create collaboration, while geographical distance deters hospitals from collaborating. All of these examples suggest that organisations that are more distant are less likely to collaborate; hence, geographical proximity is negatively associated with the propensity to collaborate across long distance among organisations (Bergé, 2017). Therefore, the second hypothesis is as follows:

Hypothesis 2. Geographical proximity is negatively associated with the intensity of collaboration among organisations.

Note that geographical proximity does not always lead to collaboration among organisations. Researchers show that organisations that are close to each other tend to compete more (Kilduff, 2014; Yu and Cannella Jr, 2007) or to be in a lock-in situation (Martin and Sunley, 2006). For example, using the data on day-care centres (DCCs), Baum & Singh (1994) found that organisations that provide similar services tend to compete more for clients when they are geographically proximate. Visser & Boschma (2004) showed that collaboration with proximate partners who are spatially bounded leads to a lock-in situation where organisations show a weak ability to confront with an increasing competitive pressure to such an extent that they lose their innovative capacity and are unable to respond to new competitive pressure. This effect can be mitigated when both social similarity and geographical proximity come into play.

5.2.3 Interplay between social similarity and geographical proximity

The importance of geographical proximity is a significant step in enhancing the understanding of inter-organisational collaboration among organisations, but the geographical factor alone is not sufficient to recognise the actual mechanisms by which resources are channelled across organisations. Indeed, the effect of geographical proximity on the formation of collaborative relationships among organisations has been investigated by considering various forms of proximity (non-spatial). Most of the traditional empirical studies have focused on geographical proximity defined as the spatial separation between economic actors (Gilly and Torre, 2000). More recently, however, other forms of proximity have been described theoretically (Knoben & Oerlemans, 2006; Boschma, 2005; Gilly & Torre, 2000), and their relative effects on the formation of an inter-organisational collaboration network have been tested empirically (Breschi and Lissoni, 2009). Beyond geographical proximity and social similarity, Boschma (2005) identified other dimensions of proximity, namely cognitive proximity, organisational proximity, and institutional proximity. Cognitive proximity is defined as the degree of similarity in the set of knowledge that organisations hold. Institutional proximity refers to the degree of similarity in terms of institutional rules, as well as a set of cultural habits and values. Organisational proximity is defined as 'the extent to which relations are shared in an organisational arrangement, either within or between organisations. This involves the rate of autonomy and the degree of control that can be exerted in organisational arrangements' (Boschma, 2005:65). Each form of proximity is thought to facilitate communication, symbolic and material resources exchange, and increase the probability to collaborate between partners.

In empirical research, it has been observed that geographical and other forms of proximity tend to be positively correlated, probably reflecting the fact that geographical distance facilitates the development of other forms of proximity. Using the data on collaboration networks in the Global Navigation Satellite System Industry, Balland (2012) examined the role of the five dimensions of proximity on the formation of collaborative ties. He found that organisational, geographical, social and institutional proximities are positively correlated with the creation of new relationships, except for cognitive proximity, which is not significant. Using the data on co-publications, Hardeman, Frenken, Nomaler, & Ter Wal (2014) investigated how these dimensions affect the probability to collaborate between organisations in different countries. They found that geographical, social, and organisational proximities play a marginal role in Europe as compared to North America, while cognitive and institutional proximities matter for the formation of collaborative ties in Europe and North America. These studies illustrated that

once the other forms of proximity are taken into consideration, geographical proximity turns out to play a more marginal role.

In examining the role of geographical and the other forms of proximity, scholars have investigated the effect of geographical proximity and social similarity, i.e. physical versus social space (Bergé, 2017; Ter Wal, 2013; Reagans, 2011; Sorenson & Stuart, 2008). As mentioned in the introduction, the aim of this study was to empirically assess the interplay between geographical proximity and social similarity in explaining the formation of collaboration network ties among organisations.

Researchers have assumed that the creation of collaborative relationships is more likely to occur when organisations are geographically proximate. This happens because geographical proximity reduces coordination costs and stimulates the creation of trustful relationships through repeated activities with the aim of transferring resources (Balland, 2012). However, the extent to which this is true is an empirical question, and empirical evidence suggests that 'social relations between distanciated partners facilitate collaboration' (Hansen, 2015:7). For example, Sorenson & Stuart, (2008) found that collaboration among geographically distant organisations increases with the establishment of social relationships among network partners. Ter Wal, (2013) showed that the effect of geographical proximity decreases over time, as organisations that are close in social space (i.e. triadic closure) are more likely to form collaboration ties among distant partners. Given these empirical observations, the expectation about the moderating role of social similarity can be formulated. Social similarity may reinforce the advantage of being geographically distant. In particular, in cases where organisations may test for similarity, social similarity can foster collaboration in situations wherein structurally equivalent organisations come to have the advantage of similarity in their patterns of relationships with third-party organisations (Lorrain and White, 1971). This search of similarity can be seen as a need to be close in the relational profile to exchange resources more effectively. In this case, organisations develop network ties with partners that are relationally proximate depending on the structural positions in the network as a whole (Burt, 1987).

In contrast, social similarity may decrease the effect of geographical proximity. As network ties are seen as the vehicle by which resources are exchanged (Gulati and Gargiulo, 1999), organisations exchange their resources within the network space. Structurally equivalent organisations occupy similar positions in the network structure, although they do not

necessarily interact with each other. This means that organisations that occupy similar network positions are more likely to exchange their resources even if they are not geographically proximate in a physical space, because resources are passed through the relationships within the global network. Hence, network positions mediate the effect of geographical proximity on resource transfers. Therefore, the third hypothesis is as follows:

Hypothesis 3: The negative effect of geographical distance (proximity) on inter-organisational collaboration decreases as the social similarity increases.

5.3 Empirical Setting and Data

5.3.1 Empirical Setting

The empirical part of this paper relies on longitudinal data on collaborative patient transfer relations observed over four-year period between 110 hospitals providing healthcare services in Lazio. Hospitals are located, from a geographical and administrative point of view, within Local Health Units (LHUs). There are 12 LHUs within the Lazio Region, 8 of which are concentred in the capital city – Rome – and the remaining 4 LHUs are located in the other four provinces of the Region – Rieti, Latina, Viterbo and Frosinone. The population of regional hospital organisations is particularly suitable for the purpose of this study for two main reasons. In the healthcare sector, the process of collaboration (and competition) is generally localized because the delivery of healthcare services is within a particular geographic locality (Lomi and Pallotti, 2012). Second, patient transfer relations (i.e. collaboration) are affected by the geographical distance between hospitals (Amati, Lomi and Mascia, 2019). Hence, geographical proximity, (competition) and collaboration are relevant factors connected to the hypotheses of this work.

Patient transfer relations have been defined and examined in previous studies as a form of inter-hospital collaboration (Kitts *et al.*, 2017). It is important to emphasize that the decision to transfer patients is ultimately a hospital decision to involve other hospitals in the joint solution of medical problem; and that hospitals are free to select which hospital to choose to transfer a patient. In making this choice, consideration about geographical distance, hospital bed capacity, as well as hospital technologies and services are all factors that are taken into account.

5.3.2 Data

As described in chapters 3-4, data on patient transfers, as well as on a number of hospital characteristics, such as number of staffed beds, number of discharges, hospital performance were provided by the Regional Hospital information System database (SIO), managed by the Public Health Agency of Lazio. The population under study includes all private and public acute care hospitals located within the regional community – Lazio as listed in the annual reports "Data Admission for elective patients" from 2006-2009. Data on patient transfers and hospital characteristics were codified in a dyadic dataset.

5.3.3 Variables and Measures

In this section, I will describe and define the dependent and the main variables of theoretical interest that are included in the model specification. All the variables are centered where all values are subtracted from the mean. This is done as while interpreting the intercept, 0 values for predictor variable does not have any meaning. Also, the interpretation of the intercept is now the mean of the dependent variable. When the variables are centered, the coefficients differ, however, the slope of the line remains the same.

5.3.3.1 Dependent Variable

The dependent variable under investigation is collaboration which is measured by considering the number of patient transfers between each pair of hospitals in the sample. The number of transferred patients is used as a proxy for the strength of collaboration between hospitals.

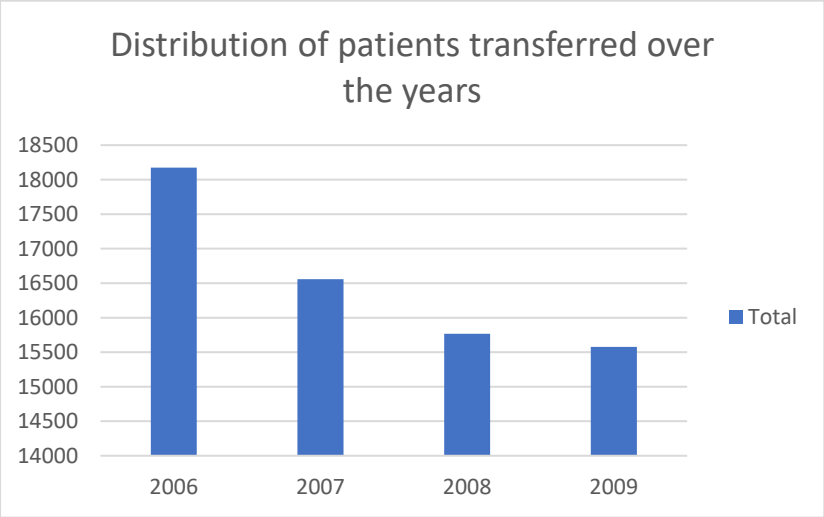
Over the periods 2006-2009, the number of patient transfers between hospitals in Lazio community, is 1867. This variable is a (non- negative) count and varies from 0 to 774. The table 17 reports the descriptive statistics, for example the average number of patients is 8.150 in 2006 and it remains stable over time. Figure 2 shows the distribution of patient transfers between hospitals over time.

Table 17: Summary of patient transfers

Year	Time	Mean	Std.dev	Min	Max
2006	1	8.150	26.882	0	774
2007	2	7.546	21.153	0	360
2008	3	7.490	20.603	0	334

2009	4	7.684	19.624	0	399

Figure 21: Distribution of patient transfers between hospitals over time by using the valued matrices



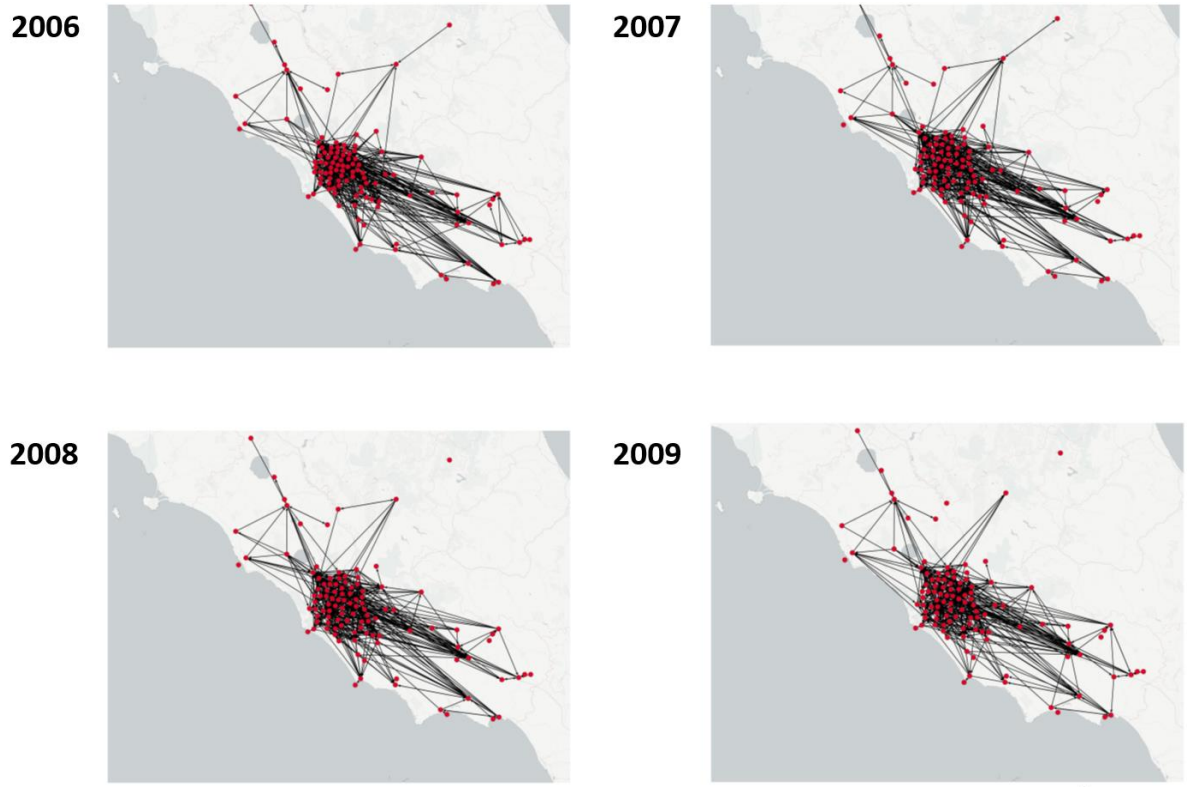
Comparing the relationships in 2006 to all other years the percentage of relationship that have been maintained are computed (keeping the 2006 as benchmark). By calculating this, it can be seen that of the 2230 inter-hospital patient transfer relations in 2006, over 90% were maintained in 2009 as shown in the table 18 – the table shows the persistence of relations among hospitals overtime.

Table 18: The persistence of ties overtime

	2006	2007	2008	2009
2006	100 %	98.43	94.03%	90.94%
2007	-	100%	92.34%	92.34%
2008	-	-	100	96.29%

When plotted the patient transfers network in Lazio for the years 2006 to 2009 (figure 22), it clearly shows that hospitals are highly agglomerated in the capital city. As a consequence, patient transfers tend to be highly localized around these hospitals. However, patient transfers also occur between hospitals that are far apart.

Figure 22: Patient transfers network in Lazio



For this study, the dependent variable is lagged to take into account that the number of patients transferred in each time period may depend on the number of patients transferred in the previous time, capturing some form of time dependency.

5. 3.3.2 Independent variables

Social similarity. The first independent variable of theoretical interest is social similarity. It is measured as structural equivalence. It captures similarity in the relational profiles between any pair of hospitals by occupying the same network position in the whole networks. I rely on the original insight of White et al. (1976) and follow a strategy that is frequently used in the block model analysis of interorganizational fields (Pallotti et al., 2015; DiMaggio, 1986). As a continuous measure of positional similarity I use the correlation of the rows and the columns of the patient transfer networks, a widely accepted continuous measure of similarity in the relational profile of organisations in the networks (Wasserman and Faust, 1994). The result is a matrix S of correlation coefficients in which the value of the cells (Sij) varies between –1 and

+1. The closer Sij is to +1, the more *i* an *j*, have similar relational profiles the more they are structurally equivalent[6].

Geographical proximity. The second independent variable of theoretical interest is geographical proximity. Geographical proximity is measured as distance in kilometres between each pair of hospitals in my sample. This variable is time independent and its values do not change over time.

Moderation effect of social similarity. The third independent variable of theoretical interest is the interaction term between geographical distance and social distance. It is created by multiplying geographic proximity and social similarity together. This variable is used to test the moderating role of social similarity in the relation between geographical distance and collaboration.

The table 19 reports the descriptive statistics of structural equivalence over the observation period.

Table 19: Summary of structural equivalence

Year	Time	Mean	Std.dev	Min	Max
2006	1	0.0747	0.1438	-0.066	1
2007	2	0.0707	0.1341	-0.072	1
2008	3	0.0678	0.1349	-0.061	1
2009	4	0.0707	0.1349	-0.069	1

It should be noted that the correlation among the two main independent variables, e.g. social similarity and geographical proximity and the dependent variable, e.g. inter-organisational collaboration is low as shown in table 20.

Table 20: Correlation table of patient transfers, geographical proximity and social similarity, obs=45828

	Patient transfers	Geographical proximity	Social similarity
Patient transfers	1.0000		

[6] The relational profile similarity measures that I compute is identical to the initial matrix of correlation produced by CONCOR, a widely known algorithm used to partition the networks into structurally equivalent sets of nodes (Arabie et al., 1978). I do not use CONCOR because I was interested in a continuous measure of similarity in network positions rather than in a discrete partition.

Geographical proximity	-0.1010	1.0000	
Social similarity	0.0872	-0.2942	1.0000

5. 3.3.3 Control variables

The empirical model includes control variables that account for other proximity dimensions and factors that can affect collaboration among hospitals. These variables fall into two main categories: dyadic and monadic variables.

Dyadic variables

Competitive interdependence. This variable measures the level of competition between each pair of hospitals in the sample. This variable has been used extensively in previous studies on healthcare (Mascia et al., 2017; M. Sohn, 2002; 2001). The level of competition is computed by measuring overlaps in patient pools as suggested by M. Sohn (2002). This variable is included in the model to control for the possibility that hospitals competing for the same resources, i.e. patients, are less likely to collaborate.

Service complementarity. This variable considers the set of clinical services (specialties in my case) that hospitals hold. It is measured by using Euclidean distances on the hospitals (n) by (m) specialties matrix. It may be seen as measuring cognitive proximity. Cognitive proximity refers to the degree of similarity on the set of knowledge activities held by organisations (Huber, 2012). In my case, clinical specialties can be seen as knowledge sets, or pools held by hospitals. This variable is included in the model to capture the extent to which two hospitals that are similar in terms of knowledge are more likely to collaborate.

Monadic variables

LHU membership. This variable indicates the membership to a specific Local Health Units (LHUs) in which the region is partitioned. This is a categorical variable range from 1 to 12 (1=RmA; 2= RmB; 3=RmC; 4= RmD; 5=RmE; 6= RmF; 7= RmG; 8=RmH; 9=Viterbo; 10=Rieti; 11=Latina; 12=Frosinone). It may be seen as measuring organisational proximity. Organisational proximity refers to the set of norms that facilitates the development of collaborative relations (Knoben and Oerlemans, 2006). This variable is included in the model

to control the extent to which hospitals that face the same administrative constraint are more likely to collaborate.

Organisational form. This variable considers the institutional diversity of hospitals in terms of their ownership-governance. It is a categorical variable range from 1 to 6 (1= Hospital trust; 2= LHU hospital; 3= University hospital; 4=National institute for scientific research; 5= Classified hospital; 6 = Private accredited hospital). It may be seen as measuring institutional proximity. Institutional proximity refers to the institutional constraints and ownership structure shared by organisations (Balland, De Vaan, & Boschma, 2012; Ponds, Van Oort, & Frenken, 2007; Boschma, 2005). This variable is included in the model to control the extent to which hospitals that have different institutional categories and ownership structure may affect the tendency of hospitals to collaborate.

Rome. This is a binary variable that takes a value of 1 if a hospital is located in Rome and 0 otherwise. This variable is included in the model to capture the extent to which hospitals that are located outside and within the urban area of Rome are more likely to exchange patients.

Hospital size. This variable measures the size of hospitals in terms of total number of staffed beds. This variable is included in the model to control for the extent to which larger or smaller hospitals are more likely to exchange patients.

Task complexity. This variable measures the complexity of cases treated by hospitals in terms of percentage of surgical DRGs over the total DRGs. It refers to admissions of patients with medical conditions that make their cases more complicated than those of the typical patients (Bellavia *et al.*, 2012). This variable is included in the model to control for the extent to which hospitals that are less or more able to deal with complex cases may affect their tendency to collaborate.

Readmission rate. This variable indicates the percentage of patients treated who are readmitted in the same hospitals for the same pathology within 30 days from discharge. It is used by the hospital managers to assess the quality of the treatment offer by hospitals. It has been used extensively in previous studies (Lomi et al., 2014; Coffey et al., 2012).This variable is used in this work to control for that extent to which hospitals that are less or more able to use their resources may affect their tendency to collaborate.

All the continuous variables are entered in the model as sender, receiver effects. All the binary and categorical variables entered the model as exact matches (except for the binary variable "Rome" that entered as sender and receiver effects).

Table 21 reports the descriptive statistics and definition of all variables included in the empirical model specification.

Table 21: Variables included in the model: definitions and descriptive statistics (row data)

VARIABLE	DEFINITION	TYPE	CONSTRUCT	DESCRIPTIVES			
				Mean	**St.Dev**	**Min**	**Max**
Dependent variable							
Patient transferred	Number of patients transferred between each pair of hospitals	Integer	Inter-organisational collaboration relation	1.441	10.106	0	774
Main independent variables							
Geographical proximity (dyadic)	Distance (in kilometres) between every pair of hospitals	Real	Geographical proximity	50.263	40.202	0	222.59
Structural equivalence (*dyadic*)	Correlation of the rows and columns of the inter-hospital patient transfers network	Real	Social similarity	0.071	0.137	-0.072	1
Interaction effect	Moderator effect computed by the independent variable (Geographical proximity) and the moderator variable (Social Similarity)	-	Moderating the effect of social similarity	-	-	-	-
Control variables							
Lagged patient transferred	Number of patients transferred between each pair of hospitals	Integer	Inter-organisational collaboration relation	1.477	10.590	0	774
N. beds (*monadic –entered as Sender and Receiver effects*)	Total number of staffed beds	Integer	Size	205.41	271.36	0	1906
Complex DRG (*monadic- entered*	Surgical DRGs over the total	Real	Complexity	0.429	0.283	0	1

as Sender and Receiver effects)	amount of DRGs (in percentage)						
Readmission rate (*monadic- enter as Sender and Receiver effects*)	Percentage of patients treated who are readmitted in the same hospitals for the same pathology within 30 days from discharge	Real	Performance	0.028	0.035	0	0.328
LHU membership (*monadic*)	Membership to local health units (LHUs)	Categorical	Organisational proximity	-	-	1	12
Organisational form (*monadic*)	Type of ownership-governance structure	Categorical	Institutional proximity	-	-	1	6
Competitive interdependence (*dyadic*)	Patient pool overlaps between every pair of hospitals as measured by Sohn (2002)	Real	Dependencies on (common) resources	0.118	0.175`	0	0.811
Rome *(enter as receiver effect)*	Binary variable taking the value of 1 if a hospital is located in Rome, and 0 otherwise	Binary	Metropolitan Area	0.509	0.500	0	1
Complementarity *(dyadic)*	Complementarity in the range of services measured as Euclidean distance on the hospitals (n) by (m) specialties matrix	Real	Service complementarity across specialties	3.221	1.079	0	6.245

5.4. Empirical model specification

I used a dyadic panel model. The dataset is dyadic because each observation is associated with pairs of entities in the sample: H*i* H*j*. The dependent variable is dyadic, measuring the number of patients transferred between any pair of hospital organisations in the sample. The model is dynamic because it includes a lagged dependent variable. The panel design is used because the dyads are repeatedly observed over time. The outcome is a non-negative count variable ($Y_{ij,t}$), where the mean is a function of the lagged dependent variable ($Y_{ij,t-1}$) that takes into account the time persistence, and of regressors (X_t). Consequently, I use a Poisson model with

exponential feedback estimated by the Generalized Method of Moment – GMM – as suggested by the econometric literature (Cameron and Trivedi, 2013) and clustered the standard errors at the sender level. The empirical model adopted in this study takes the following form:

$$E(Y_{ij,t}) = exp(\rho Y_{ij,t-1} + \beta_1 X'_{ij,t\ t} + \beta_2 X''_{ij,t} + \beta_3 X'_{ij,t} X''_{ij,t} + \delta X_{ij,,t})$$

where $Y_{ij,t}$ is the number of patients transferred between hospital *i* and hospital *j* at time; $Y_{ij,t-1}$ is the one period lagged dependent variable; $\beta_1 X'_{ij,t}$ is the geographical proximity between hospital *i* and hospital *j*; $\beta_2 X''_{ij,t}$ is the social similarity between hospital i and hospital *j*; $\beta_3 X'_{ij,t} X''_{ij,t}$ is the interaction effect for geographical distance and social similarity; $X_{ij,t}$ summarizes the effect of covariates in the model specification, which may refer to Sender *i* (for example the size of the sender hospital), to *Receiver j* (for example the size of the receiver hospital) or both (for example complementarity). Regarding parameters, ρ is the effect of the lagged dependent variable, capturing the inertia in the exchange relations; the β measure the strength of the variables of theoretical interest; and δ measures the effects of control variables. Because the data are dyadic, continuous organisational covariates, (i.e. number of staffed bed) entered into the model as sender and receiver effects. For covariates taking categorical (i.e. Organisational form) and binary values an exact match is used to identify hospitals in the same category.

In this section, GMM approach for count data is briefly introduced and its usefulness for the analysis of the data is discussed along with its limitations.

5.4.1 General Methods of Moments Estimation for count data

Model for count data has been used in many fields, for example in health economics (for a review of econometrics models for health care data, see Jones, 2009), inter-organisational networks (Stuart and Sorenson, 2003), and economics geography (Scherngell, Borowiecki and Hu, 2014). When the dependent variable of interest is count and error distributions tend to be skewed because zero bounds the lower end of the observed range, researchers often employed a Poisson regression (Greene, 2007). The Poisson regression model is an example where the conditional mean function is modelled to be exponential (Windmeijer, 2006). Recently the interest in exponential regression models for panel count data has been grown exponentially with the use of the General Method of Moments – GMM- as estimation procedure (Cameron & Trivedi, 2013; Wooldrige, 2010). The GMM allows the treatment of unobserved individual heterogeneity that is correlated with the explanatory variables. The GMM is built on the

classical method of moments, which uses the assumption stating that a parameter can be estimated by replacing a population moment condition with its sample analogue. The GMM also permits to treat unobserved individual heterogeneity that is associated with the main variables and when the main variables are not exogenous. It also permits to use instrument variables that are "internal" in the non-linear equation i.e. based on laggedness of the instrumented variables (Cameron and Trivedi, 2013). The estimator is available in Stata as *gmm* command allowing for the specification of the particular lag variable to be included in the model. In contrast with other models that not including the lagged dependent variable, this model permits to separate between the state dependence and unobserved heterogeneity. That is, in my work, between cases in which hospitals *i* and hospitals *j* create new collaborative relations today, because they have already collaborated in the recent past or because they have a particular propensity for collaborating with each other.

5.4.2 Estimation strategy for network data

Modelling network data is a challenge because observations are dependent because each entity in the network matrix appears in multiple dyads, thus creates a complex dependency across observations (Stuart, 1998). Under these conditions, coefficient estimates will still be consistent, but the presence of complex dependence structures may lead to under-estimation of the standard errors. In empirical studies of inter-organisational networks, this problem is typically alleviated by clustering the standard errors on the sender (the initiator of a tie) and applying the Hubert-White correction for heteroskedasticity (Powell *et al.*, 2005; Reagans and McEvily, 2003; White, 1980). This analytical strategy also serves as a control for additional sources of unobserved heterogeneity across actors. Accordingly, I adopt the same analytical strategy by clustering on the first entity in each dyad, i.e. $H_{i,}$. This strategy is also aligned with the idea assumption that there is agency inherent to patient transfers. Patient transfers are outcome of coordinated activities between sender and receiver hospitals in order to find a common solution of medical problem. Patient transfers initiative are usually taken by the sender who makes the decision to select potential partners.

5.5 Analysis

Table 8 reports the results of the model specified in the previous section. Models are reported in the increasing order of completeness. In particular, Model 1 includes only the lagged dependent variable and the geographical proximity variable. Model 2 introduces the effect of social similarity. Model 3 introduces the interaction effect between geographical proximity and social proximity. Finally, Model 4 reports the full model, including the control variables. The discussion of the results with respect to the full model (Model 4) is summarised in Table 17.

Hypothesis testing

Overall, the results support the research hypotheses, where the effects of geographical distance and social distance were significant in the expected directions. Concerning the hypothesis that examined the role of geographic proximity, Model 4 showed that the effect of 'geographical proximity' (Hypothesis 2) is negative and significant, suggesting that hospitals are more likely to collaborate across short distances over time. The significantly positive parameter for 'social similarity' (Hypothesis 1) suggested that hospitals that occupied the same network positions by sharing the same relational profile were more likely to establish collaborative relationships over time. In other words, the more similar the hospitals were in their position, the higher was their propensity to collaborate. The significantly positive parameter for the interaction effects between 'social similarity' and 'geographical proximity' (Hypothesis 3) suggested that social similarity moderated the relationship between geographical proximity and collaboration. To interpret the results more intuitively, inter-hospital patient transfers and geographical proximity were plotted for high and low positional similarity (figure 23). High and low positional similarities were calculated using the average of the structural equivalence ± 1 SD (standard deviation) as the cut-off value.

Table 22: Dynamic panel with count data –estimated by GMM-

Variable	Model 1	Model 2	Model 3	Model 4
Lagged patient transfers	0.0092***	0.0089***	0.009***	0.0089***
Geographical proximity	**-0.0202*** **	**-0.0176*** **	**-0.0183*** **	**-0.0213*** **
Social similarity		**1.7877*** **	**2.553*** **	**1.8516*** **
Geographical proximity * Social similarity			**0.0277*** **	**0.0313*** **
Competitive interdependence				0.2232
Service complementarity				0.2035*
Hospital Size (Sender)				0.0013***

Hospital Size (Receiver)				0.0012***
Readmission Rate (Sender)				-7.0336
Readmission Rate (Receiver)				-2.6736*
Surgical Diagnosis(Sender)				-0.5976
Surgical Diagnosis(Receiver)				-0.8499**
Rome (Sender)				-0.7967*
Rome (Receiver)				-0.1227
LHU membership				0.8466***
Organisational form				0.1175
N	*33838*	*33838*	*33838*	*33838*
Hansen test of overid.restrinction				*chi2(1) = 1.84 Prob > chi2 = 0.397*

Legend: * p<0.05; ** p<0.01; *** p<0.001

Figure 23: Moderating effect of social similarity on the geographical distance and inter-organisational collaboration - two-way interaction with continuous moderator

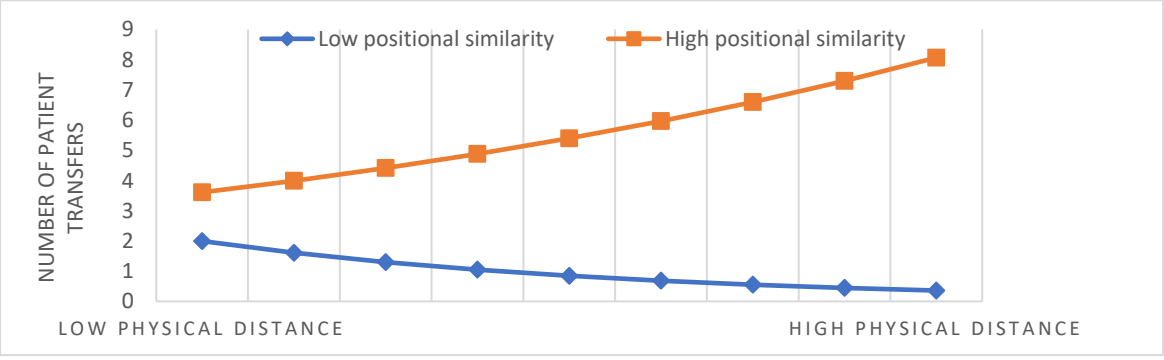


Figure 23 shows the plot of the interaction effect. It shows that the relationship between geographical distance and exchange is negative (blue line) for low levels of positional similarity. For high levels of positional similarity (orange line), the relationship turns positive. In other words, when organisations are geographically proximate, the positional similarity does not matter with respect to the exchange resources (low physical distance). However, when organisations are geographically distant, the positional similarity matters with respect to the exchange resources (high physical distance). Thus, this suggests that the positional similarity increases as the distance increases, and hence, it is more important than the geographical distance with respect to the propensity of hospitals to collaborate, i.e. exchange patients.

Control variables

Model 4 also showed the effect of the control variables. Hospitals with a similar set of specialties were more likely to collaborate (positive effect of service complementarity), implying that cognitive proximity affected the formation of exchange relations. Hospitals that belonged to the same administrative area (LHUs) were significantly more likely to collaborate (positive effect of LHU membership), meaning that organisational proximity facilitated the establishment of collaborative relationships. Larger and smaller hospitals were more likely to exchange patients and hence, to collaborate (positive effects for both sender and receiver hospitals). Hospitals were more likely to be selected by partners if they were more capable of treating complex cases (positive effect of receiver surgical diagnoses) and more capable of managing their resources (positive effect of receiver readmission rate). Hospitals were more likely to send patients to a hospital within Rome (positive effect of sender Rome). The predicted effects of social similarity and geographical proximity on the formation of collaborative ties remained virtually unchanged after controlling for the control variables.

5.6. Discussion and Conclusions

In the existing literature, it has been argued that geographical proximity facilitates the establishment of collaboration between organisations, but also other forms of proximity positively affect tie formation, i.e., organisations that are socially proximate are more likely to collaborate. Building on the existing literature, the results obtained in this study contribute to this stream of research by investigating the dynamic interplay between social similarity and geographical proximity as the two factors explaining the formation of collaborative ties among organisations overtime. The motivation behind the idea of testing the interaction effect of geographical proximity and social similarity was to understand the importance of network-related mechanisms that triggers collaboration among organisations. The first mechanism that plays a role in network evolution is similarity in network positions, i.e., structural equivalence. Two structural equivalent organisations are socially proximate to the extent that they have the same pattern of relations with organisation of other positions (Burt, 1987; White & at al.,1976). This can be an advantage for the establishment of future collaborations because if two organisations are connected to the same partners they are more likely to be in some way relational similar to their common collaborator and consequently to share some similarities themselves. Second, two structural equivalent organisations are more likely to have similar opportunities, benefits and constraints whereby the network can act as a reliable channel of

information in which organisations can find information about their potential collaborators (Gulati and Gargiulo, 1999).

Taking the inter-organisational collaboration networks of hospitals in Italy as the empirical setting, I drew three main conclusions from the results of the present study. First, I found that proximate hospitals tended to exchange patients and hence, begin to collaborate. This result was in agreement with the existing literature that emphasises that organisations tend to choose proximate partners (Broekel, 2015; Balland, 2012). The present study also confirmed the findings of other empirical studies on inter-organisational collaboration in healthcare (Mascia, Pallotti and Angeli, 2017; Amati, Lomi and Mascia, 2019), and more generally, the idea that inter-hospital collaboration via patient transfers involves geographical proximity and face-to-face interactions. Second, I found that social similarity facilitated the establishment of collaborative relationships. The idea of structural similarity indicates that two structurally equivalent organisations are in similar structural positions in the network, although they do not necessarily interact with each other. This means that organisations prefer to collaborate with other organisations that are perceived to be socially proximate with respect to their relational profile (Burt, 1987). This result was in agreement with the literature on inter-organisational collaboration in healthcare, with the general idea that being closer in a social space encourages hospitals to collaborate over time (Hollway *et al.*, 2017). Third, testing the interaction effects between geographical proximity and social similarity showed that social similarity moderated the effect of geographical proximity. This meant that the more the organisations were socially close, and hence, perceived as similar, the higher was the probability to form network ties between distant partners.

Besides the theoretical argument which explains that social similarity facilitates collaboration among organisations, the idea of structural equivalence indicates the intensity of competition among organisations -(Burt, 1992, 1987). In a seminal paper Burt (1987) suggested that relying on the same partners (i.e., sources of resources) leads to competitive pressures among organizations whereby organisations. In other words, the more similar ego's and alter's ties with others are – that is, the more an alter could substitute ego's position in the network the more intense will be the competition between ego and alter (Burt,1987). The main implication is that structural equivalence gives arises two different yet interwoven mechanisms: similarity (in structural positions) and competition. As discussed above, the results showed that the negative effect of geographical distance on the formation of network ties decreased for a higher level of structural equivalence, i.e. competition. It has been argued that collaboration between

organisations typically decays with an increasing level of competition between proximate organisations (Kilduff, Elfenbein and Staw, 2010; Yu and Cannella Jr, 2007), but it can alternatively happen that coopetition occurs across a long distance depending on the network positions that organisations come to occupy. In other words, the more two organisations compete, the more they collaborate. Therefore, competition fosters the creation of collaborative ties across long distances.

This study makes significant contributions to the existing literature. First, this paper contributed to the on-going debate on proximity perspective and inter-organisational collaboration networks. There have been studies stressing on the role of networks and the role of geography, but few studies have unfolded their interplay (Bergé, 2017; Mascia et al., 2017; Ter Wal, 2013; Reagans, 2011; Sorenson & Stuart, 2008). The way geographical proximity affects the creation of an inter-organisational collaboration network was shown to be negative and constant over time. Remarkably, given the direct effect of geography, it left a lasting imprint on the spatial patterns of collaboration, as the network positions might reinforce the localised collaboration patterns. Second, even if this study was mainly oriented toward an empirical analysis, the major issue was to 'test theoretically' the definition of social similarity. The network position configuration accounted for the general level of interactions that helped to fully understand the exchange. This, in turn, allowed me to understand how the network position could moderate geographical proximity. The tendency to collaborate with partners who were geographically proximate could not exclusively be explained by localised collaboration patterns, as these were the results of the network position where geographic factors and the overall characteristics of network interplayed.

5.6.1 Limitations and future research

This study has three important limitations, which also provide open perspectives for future research. First, the findings of this work are limited to the idiosyncratic nature of the healthcare setting. This raises the question to what extent the results can be extended to other sectors. The way in which the interplay between geographical proximity and social similarity unfolds over time may well apply to other sectors, as the nature of collaboration changes during different sectors. It is still not clear how organisations can collaborate and how the impact of network differs across industries over time.

Second, this article only provided "one meaning" for geographical distance and its role in the propensity to form a tie between organisations. Although, I conducted preliminary post hoc analysis to investigate the robustness of my findings and to understand the relationship between geographical and social and proximities. More specifically, I repeated the analysis by considering the linear feedback to model the data and the results and interpretation were entirely consistent with those presented above (see the appendix B): the negative effect of geographical distance tends to decrease as similarity in network positions increases. Future research could systematically re-test the findings for other meanings of geographical proximity, by considering the driver distance[7] as the relative distance between social actors. This may offer an additional insight into the specific nature of this dimension.

Third, this work has only provided one way to look at social similarity by using structural equivalence. I stressed on the role of structural equivalence as measure of relational similarity (in terms of relational profiles) and I only considered only one dimension (i.e. organisations occupy similar positions within the network as whole) of this concept. This may be simplifying the complex nature of healthcare sector. An important direction for future researchers would be to broaden the range of positional similarity. Sociology offers a much wider array of investigating positional similarity (Mizruchi, 1993), - i.e. regular equivalence - than structural equivalence alone that have potential theoretical relevance for the dynamics of collaboration and inter-organisational network. Furthermore, patients are only important resources for hospitals. Hospital may collaborate in various way, such as medical and managers sharing, or through joint training programmes for healthcare professionals. Exploring all possible relations among hospitals may offer new answer to the following question: what makes collaboration between healthcare providers more likely to occur?

[7] The choice of using kilometres to measure geographical proximity is related to the specific characteristics of the region/ setting in my study. However, I also used the driver/travelling distance as robustness check and the results do not change.

Chapter 6: Who benefits from whom: How resource complementary and spatial location affect collaboration network dynamics

Abstract

Organisations typically establish collaborative relationships with other organisations with the aim of getting access to resources possessed by others. The extant research suggests that resource complementarity is one of the main drivers of the partner selection decision: organisations select partners that have different set resources in which the combination of resources is valuable. Recently, research has distinguished between depth complementarity, which is the overlap of the same types of resources held by organisations, and scope complementarity, which is the overlap of different types of resources possessed by organisations. However, empirical studies rarely specify the relational mechanisms that link the change in network ties to the evolution of network structures with respect to the resources complementary. This paper focuses on the effect of resources complementary held by partners on the dynamic of collaborative relationships among organisations. More specifically, this study adopts the distinction between scope and depth resources complementarity to examine the interplay between resources complementarity and geographical location on the dynamic of inter-organisational networks. This study uses stochastic actor-oriented model (SOAMs) to investigate the network dynamics of the inter-organisational networks and the impact on the decision-making behaviour of organisations. An empirical analysis of inter-organisational collaboration within a small regional community of hospitals reveals that the effect of resources complementary is contingent on the geographical location of the organisations and at the same time collaboration induced by resources complementarity affects organisational performance.

Keywords: Inter-organisational networks, resource complementarity, spatial location, Stochastic actor oriented models.

Highlights

- Exploring the relationship between resource complementarity and geographical location on the dynamic of inter-organisational networks
- Testing empirically the effects of scope and depth complementarity on the dynamic of inter-organisational networks
- The effect of resource complementarity is contingent on the geographical location of hospital organisations
- Collaboration induced by resource complementarity impacts on organizational performance

6.1 Introduction

In recent years, there has been an increased interest in the areas of decision making of organisations and the governance mode. A decision is crucial to organisations, and the effective management of decisions ensures that organisations are capable of enduring coordination costs that support their portfolio product scope strategy and remain competitive (Novak and Wernerfelt, 2012). Scholars have paid attention to the study of the portfolio product strategy through the lens of multiple industries (Palich, Cardinal and Miller, 2000) or through a single industry (Hashai, 2015) and how this affects organisational performance.

Recently, researchers have started to investigate the portfolio product scope strategy through the lens of complementarity and how this has impacted the governance mode and performance (Lee and Kapoor, 2017). Complementarity is defined as the combination of set resources in which one resource increases the values of others (Ennen and Richter, 2010). Using the data on the healthcare sector, Lee & Kapoor (2017) find that hospitals with a narrow portfolio of activities tend to have contracts with external physicians, while hospitals with a wide portfolio tend to have contracts with their own physicians. They also report that the integration of complementarity activities is considered a preferable mode of governance, because a broader product portfolio increases the coordination costs for organisations.

This theoretical insight is perhaps the most comprehensive empirical articulation in the research on inter-organisational networks (Soda & Furlotti, 2017; Gulati & Gargiulo, 1999). On one hand, two organizations adopt the same behavioral or preferences of their partners if

they are connected by network ties. Network ties generate mutual awareness and create favorable conditions to the development of collaborative arrangements aimed at supporting influence, imitation and learning that affect organizational outcomes (DiMaggio and Powell, 1983). Empirical evidence support of this perspective has been strong: organizations assimilate the strategy of their partner (Greve, 1997); adopt the same behavioral orientation (Galaskiewicz and Wasserman, 1989). On the other hand, two organizations develop network ties with diverse partners or partners holding different, i.e. resources complementary (Furlotti and Soda, 2018). Accordingly, different organisations interact, sharing resources and capability with each other in other to fill organisation gaps (Gulati and Gargiulo, 1999). However, the existing literature has provided little guidance on how resource complementarity should be operationalised (Soda and Furlotti, 2018; 2017).

The exchange of resources also depends on the consideration of the geographical location among potential partners (Powell *et al.*, 2005). This happens because geographical location affects the evolution of inter-organisational networks by defining a social and economic setting conducive of relational coordination and resource exchange among the co-located organisations (Saxenian, 1994). Geographical location is evaluated with respect to resources controlled by partners that may be able to contribute to their potential collaboration (Reuer and Lahiri, 2013). In general, resources exchange are expected to exist among organisations that are co-located in a geographic cluster (Rothaermel, 2002). Co-location in a geographic cluster is defined as "a geographically proximate group of interconnected firms and related institutions in a particular field" (Ryu et al., 2018:947). Co-location in a cluster increases resources exchange not only due to geographic proximity but also through the different services hold by different organisations (Almeida & Kogut,1999). Therefore, the geographic co-location between partners is an important factor that affects resources exchanges and consequently impacts organisational behaviour (Gulati & Singh, 1998). However, the existing literature has seldom investigated the effect of complementarity when organisations are partnered with clustered organisations (Yang, 2018).

Although previous research has provided valuable insights on resources complementary, there are several gaps in the literature. Firstly, research in the field of strategy and multiproduct portfolios posits that while factors such as portfolio composition and the governance mode affect organisational behaviour and coordination costs, the effectiveness of portfolio strategy consists of more than just the governance mode, and factors such as behaviour dynamics and relationships between potential partners need to be considered. Secondly, the investment and coordination costs are not only a result of the integration between complementarity activities

as the mode of governance and the organisation's product portfolio strategy but also a result of selection and influence processes. Thirdly, prior research has shown that inter-organisational networks affect directly organisational behaviour and performance (Ahuja, 2000). Prior research has shown that complementarity affects the formation of network ties between organisations (Ahuja, Polidoro Jr, & Mitchell, 2009; Mitsuhashi & Greve, 2009; Gulati, 1999). However few studies have distinguished between depth and the scope complementarity offered by the potential partners and how this impact organisational outcomes (Furlotti and Soda, 2018). Finally, prior research has shown that spatial structure of organisational community affects the evolutionary dynamics of inter-organisational networks. This happens because organisations establish network ties in order to manage their resource dependence (DiMaggio and Powell, 1983). Once established, network ties affect a broad range of organisational outcomes (Bell and Zaheer, 2007; Davis and Greve, 1997). To the extent that the dynamics of inter-organisational networks is affected by the geographical location of the nodes, organizational outcomes associated with the presence of network ties will also vary across geographical locations as a consequence of the general tendency of networks to "create outcomes that are, in turn, antecedents for further network development" (Brass et al., 2004: 809). However, there is limited understanding of how organisations manage their portfolio of network partners depending on the particular dimension of complementarity (i.e. depth and scope) when geographical location is also taken into account. An examination of the joint effects of complementarity and geographical location on the evolution of the network relationships among organisations will advance the understanding on the evolutionary dynamics of inter-organisational networks. Additionally, analytical methods that account for simultaneous partner choices are needed (Furlotti and Soda, 2018).

To address these gaps, the main research question that this work attempts to answer is the following: *How do resources complementarity affect the selection of collaborative partners and how these affect organisational performance?*

This is particularly relevant for understanding how organisations construct and manage their portfolio of resources, activities, and relationships (Hollway *et al.*, 2017). Recent research has indicated that the internal organisational structure (i.e. portfolio of activities) and the inter-generational networks (portfolio of network partners) co-evolve: the portfolio of organisational activities contributes to relationship formation, and the resulting networks, in turn, influence the organisations (Lomi, Pallotti and Zappa, 2018). In other words, organisations are seen as

active agents who choose to change their portfolio of activities, thereby actively shaping the portfolio of network partners and making decisions based on it. A change in the internal organisational structure, in turn, influences their actions (Amati *et al.*, 2019).

The current paper focuses on resource complementary in organisations and contributes to the debate on the changes in the inter-organisational collaboration dynamics (Majchrzak, Jarvenpaa and Bagherzadeh, 2015) by analysing the dynamics of pattern changes in collaborative networks among the organisations in different ways. In this study, I adopt and extend the previous work by Furlotti & Soda (2018) suggesting two dimensions that are linked to resources complementarity, i.e. scope and depth. In doing so, I specify the actual mechanisms through which organisations select their partners and change their portfolio of relationships and how this affects collaboration among organisations. More specifically, I show that inter-organisational networks coevolve with relevant organisational outcomes: partner selection decisions are affected by dimension of organisational performance that is influenced, in turn, by existing ties with network partners. Secondly, as co-location in a geographic cluster geographical location matters for the creation and maintenance of collaboration (van Zelst, Mannak, & Oerlemans, 2017; Reuer & Lahiri, 2013),due to the uneven geographical distribution of organisations and variations in the settlement structure. I therefore assume that spatial location and complementarity can operate differently on subset of organisations present in different locations. Prior research has shown that organisations are spatially heterogeneous (Lomi, 1995) and that social selection and social influence processes depend on location (Whittington et al.,2009; Powel et al., 2005). In this paper, I reconstruct and test empirically the effects of scope and depth complementarity on the dynamic of inter-organisational networks in order to determine whether the effect of resources complementarity vary across spatial location. To test my hypotheses I use Stochastic Actor-Oriented models (SAOMs) as a statistical approach for analysing the identified inter-organisational networks. To the best of my knowledge, this empirical study is the first to apply SAOMs in order to examine the effect of resources complementarity on inter-organisational networks when the geographical location is also taken into account.

The opportunity to demonstrate the empirical value of this study is provided by the longitudinal data on the collaborative relationships between hospitals within a small regional community located in Central Italy. Because of the strong spatial character of their activities, hospitals—and service organisations in general—provide an ideal setting for examining how network-based processes vary across physical locations. More specifically, in this study, I use inter-

organisational collaborative relationships, via patient transfers, that connect partner hospitals (one-mode network). Hospitals vary both in their portfolios—in terms of activities and network partners—and in the way they are organised with respect to patients (Stadtfeld *et al.*, 2016). Moreover, the importance of coordinating activities through patient transfers has been strongly discussed in healthcare studies and is considered a proxy for the collaboration among hospitals (Iwashyna, 2012).

The rest of the paper is organised as follows. The next section will discuss the theoretical background of this study by showing the link between inter-organisational networks, resources complementary, and geography. The third section describes the data and the analytical strategy. The fourth section reports the empirical results of the study. The final section concludes with a discussion of the implications and the limitations of the study and emphasises how the structure of inter-organisational networks emerge through the process of resource complementary.

6.2 Theory and Hypotheses

The central question in the inter-organisational network and proximity literature on the network formation is 'Who benefits from whom?'. These studies have focused on the identification of antecedents that describe how organisations select their potential partners on the basis of their resources and their location. In a typical study, the concept of complementarity is usually described as the beneficial interplay of the set of activities of an organisation (Soda and Furlotti, 2017) and is in addition to the research that investigates the interaction between resources. The latter is addressed by, for example, understanding how resources interact with one other. An example is the strategic management research that examines how complementary activities affect the governance choices (Argyres and Bigelow, 2007) and how these affect organisational performance (Lee and Kapoor, 2017).

This study aims at understanding the role of resource complementarity and geographical location on the dynamic of inter-organisational networks whereby selection and influences processes shape the evolution of network structure and organisation behaviour.

Previous work has argued that complementary partners emerge as an inter-organisational dyadic relationship (Furlotti & Soda, 2018; Soda & Furlotti, 2017; Rivera, Soderstrom, & Uzzi, 2010; Gulati & Gargiulo, 1999) and influence the development of network ties. The present

paper further extends this approach by hypothesising and comparing the role of location effects with respect to the complementarity effects. In addition, this paper specifies the social mechanisms behind the observed forms of dyadic (and possibly, extra-dyadic) dependence linking complementary partners in the evolution of inter-organisational networks.

In line with prior research (Furlotti and Soda, 2018; Soda and Furlotti, 2017), this paper distinguishes between two types of complementary resources: depth and scope. This paper first introduces (6.2.1) the role of complementarity in inter-organisational networks. Subsection 6.2.2 describes the role of geographical location on the development of network ties. Subsection 6.2.3 introduces the joint effects of location and complementarity on the evolution of inter-organisational networks . In addition, this paper specifies the endogenous change in the dyadic and extra-dyadic links between complementary partners (Subsection 6.2.4).

6.2.1 Resource Complementary and inter-organisational networks

The idea that complementarity affects organisational behaviours could be linked to the resource dependency theory, which stresses how organisations rely on others that have the necessary resources and capabilities and thus, mitigate uncertainty (Pfeffer and Nowak, 1976). In inter-organisational network research, complementarity is defined as the combination of different attributes that generate value (Snijders and Lomi, 2019). By definition, the term complementarity emerges from a dyadic relationship between partners, whereby the marginal return of one activity increases with respect to that of the other activities (Milgrom and Roberts, 1995). Accordingly complementarity is referred to the interactions among dissimilar resources among organisations (Kale, Singh and Perlmutter, 2000), whereby complementarity provides the basis for filling gaps (Gulati and Gargiulo, 1999) and ‘rounding out’ (Zaheer, Castañer and Souder, 2013) the resources available to their potential partners.

In the existing literature, resource dissimilarity and resource complementarity are used as synonymous (Furlotti & Soda, 2017). Resource dissimilarity (or resource complementarity) occurs for several reasons. Organisations with complementary resources and specialisations in a particular field work together to perform a complex task (Soda & Furlotti, 2018). The division of labour leads to reliable partnership and diminishes competition among organisations (Baum *et al.*, 2005) while sustaining learning process among organisations (Sarkar, Echambadi, Cavusgil, & Aulakh, 2001; Powell, Koput, & Smith-Doerr, 1996). Pooling distinct types of resources can result in synergies that foster future collaboration whereby partners are more likely to complement one another (Chung, Singh and Lee, 2000). Furthermore, resource

dissimilarity enables organisations to match their capabilities with their potential partners (Furlotti and Soda, 2018; Mitsuhashi and Greve, 2009), and thus reduces the risk of mismatching. The diversity in resource endowment constitutes the basis for the assessment of resource complementarity of two potential partners (Soda and Furlotti, 2018). Complementary partners are defined as 'those who are able to provide those task-related skills and resources that are necessary to fill the capability gaps of the focal firm'(Soda & Furlotti, 2017:353).

In the existing literature resource complementarity is measured as dissimilarity in the resource's profile based on (i) the idea that organisations operating in different market niches hold different sets of resources and ii) the fact that differentiation increases complementarity and leads to interdependence between organisations (Gulati & Gargiulo, 1999). Soda and Furlotti (2018, 2017) distinguish between scope and depth resource complementarity; the former captures the advantage of pooling different type of resources and thus reflects the variety of the resources (Soda & Furlotti, 2017). For example, research shows that organisations tend to collaborate with partners that offer different set of resources because new resources are channelled and combined (Powell et al., 2005; T. Stuart & Sorenson 2003). The latter, depth complementarity, captures the advantage of pooling similar type of resources and thus reflects the intensity/ volume or quantity of resources (Soda & Furlotti, 2017). More specifically, two organisations exhibit depth complementarity at the level of a resource *j* when neither organisations "possesses the focal resource in an amount that is sufficient to perform the task: and if by pooling the focal resource, they draw nearer to, match, or exceed the depth of resource *j* required to perform the task" (Soda & Furlotti, 2017:358). For instance, research shows that organisations are more likely to be selected when they are similar in terms of strategic resources where the combination or pooling of those resources enables organisation to perform a complex task (Soda & Furlotti, 2018; Hungarian IJV, Lane, Salk, & Lyles 2001). This happens because similarity in set of resources enhances learning process because organisations are better able 'to evaluate and internalize the know-know of technologically similar firms' (Stuart, 1998:672). Pooling different and similar relevant resources can result in synergies that ultimately reduce search, coordination and governance costs (Soda & Furlotti, 2018; Garcia-Canal et al., 2003). Therefore, scope and depth complementarity tend to be positively associated with the creation of network ties (Soda & Furlotti, 2017). The presence of both scope and depth complementarity is particularly relevant in healthcare setting due the fact that diversity and similarity in the set of 'clinical activities that hospitals hold push them to integrate their capabilities in order to ensure effective healthcare (Stadtfeld et al., 2016). On

one hand, diversity in the range of clinical activities (or knowledge pools) push hospitals to transfer patients (Amati et al. 2019). Patients may be transferred when hospitals do not have a specific clinical activity and hence more appropriate treatments are needed (Lomi et at al., 2014). The diversity (or dissimilarity) of providers in terms of clinical activities specialisation is crucial for the creation od patient transfer relations. On the other hand, similarity in terms of set of clinical activities enables hospitals to learn from their partners by reproducing the operational experience of partners (Stadtfeld et al., 2016). This happens because organisations are more likely to benefit from partners with similar knowledge bases (Cohen and Levinthal, 1994). In this case, patients may be transferred for different reasons, e.g., a contingent lack of capacity in terms of staffed beds – (Tramner et al. al 2015). Dissimilar and similar hospitals collaborate to guarantee continuity of care (Zappa et al., 2018; Stadtfeld et al., 2016).

Based on the above, the two hypotheses are:

Hypothesis on scope complementarity resources (H1): A higher level of scope complementarity will increase the propensity of organisations to collaborate.

Hypothesis on depth complementarity resources (H2): A higher level of depth complementarity will increase the propensity of organisations to collaborate.

The established fact that resource complementarity bounds the formation of network ties, implies that the consequences of those same network ties will also influence collaboration across organisational boundaries. Once established, network ties between organizations affect a broad range of organizational outcomes such as innovation (Hoang & Rothermael) and performance (Baum et al.,2000) by providing access to valuable information, diffusing successful practices, and facilitating access to extramural resources and knowledge (Sacks, Ventresca and Uzzi, 2001). In a word, network ties are a fundamental source of learning opportunities (Powell, Koput and Smith-Doerr, 1996). Prior research has recognized, however, that complementarity may alter the ways in which organizations take advantage of their connections (Mitsuhashi and Greve, 2009), hence inducing resource complementarity in the potential outcomes of network ties.

6.2.2 Geography and inter-organisational networks

In addition to resource complementary of two organisations, extant research has shown that geographical location plays an important role in the formation and evolution of inter-

organisational networks (Balland, Belso-Martínez and Morrison, 2016; Morrison, Rabellotti and Zirulia, 2013). This happens because co-location reduces the number of steps of the information search process by spatially limiting the search for potential partners (van Zelst, Mannak and Oerlemans, 2017). In the biotechnology sector, for instance, intercorporate connections such as strategic alliances are more likely to be observed between firms that are physically proximate are co-located in space (Powell et al., 2005). Corporate board interlocking ties are more likely to be established among firms with headquarters in proximate locations (KONO et al., 1998). Venture capitalists firms are more likely to establish investment relations with companies that are located close to them (Sorenson and Stuart, 2001). While based on very different organizations, these studies show that information, knowledge and practices more readily diffuse across geographically proximate organizations (Jaffe et al. 1993, Almeida et al. 2003; Owen-Smith and Powell, 2004; Whittington, Owen-Smith and Powell, 2009). For example, in examining the spread of governance practices among the largest industrial corporations in the US, Davis and Greve (1997) found that some practices diffuse more rapidly when firms are located in the same geographical area. Finally, Greve (2009) found that the diffusion of production technology innovations in the shipping industry is faster among firms within the same geographical cluster. In general, these studies provide support to cluster theory which holds that diffusion processes are geographically bounded, i.e., they are typically more rapid over short distances (D'Aunno, Succi, and Alexander, 2000; Burns and Wholey, 1993; Rao, Davis, and Ward, 2000; Whittington, Owen-Smith and Powell, 2009).

Indeed, the probability of observing network ties declines with both physical and path distance between organizations (Baum et al., 2005). First, the relatively short path length that is typically observed within organizational communities may reflect the costs and risks of establishing ties with (physically) distant partners that are separated by geographical or administrative barriers. This first family of location-specific factors is evident in the healthcare setting where distance between partner hospitals increases the costs and risks of transferring patients. For instance, longer distances decreases collaboration between two hospitals due to the increased travel times for patients when hospitals are located in rural area (Lamika et al.,2016; Mascia et al., 2016). Second, environmental resources are typically localized, i.e., are not homogeneously distributed in space (Lomi, 1995) because for a given organization: "geographic location determines (...) demand for (its) output and the competition it faces" (Baum and Haveman, 1997, p. 304). Consequently, clustering in interorganizational networks may be due to spatially heterogeneity in the distribution of environmental resources. For instance, the environmental

variations and differences in the distribution of clinical services (Isaksson et al., 2015) makes difference between urban and rural areas. Multiple hospitals are often located in the same geographical areas, i.e. urban areas, where patients tend to consult the nearest hospital (Brems et al.,2006). The presence of this second family of location-specific factors is also prominent in healthcare sector because hospitals in different locations face different patterns of resource availability and demand for the services they offer. Based on the above, the hypothesis is:

Hypothesis on geographical location (H3): Co-location in the same cluster area will increase the propensity of organisations to collaborate.

6.2.3 Complementarity, geographical location, and their interacting effects on inter-organisational collaboration

As mention above, resource complementarity and geographical location are are positively associated with the formation and maintenance of inter-organisational networks. Previous research has shown that when two organisations are located in the same area, the probability to form a connection will diminish as they will have a lower degree of complementary resources. In contrast, if two organisations are located in different areas, the probability to form a connection will be higher as they will have a higher degree of complementary resources. Even if two organisations are located in the same space, the likelihood to form network ties will be less or more if they possess different resource complementarities for different reasons. First, complementarity stimulates awareness about the potential partners and makes the benefits of coordination easier to perceive (Lane and Lubatkin, 1998). Second, when organisations exhibit a certain degree of similarity in their resource complementarity, partners are more likely to sustain higher costs and reduce the negative effect of geographical distance (Reuer and Lahiri, 2013). Third, complementary resources enable organisations to access the different types of knowledge possessed by distant partners and thus avoid a lock-in (Knoben and Oerlemans, 2012). Finally, when organisations are located further apart and exhibit a certain degree of dissimilarity in their resource complementarity, distant partners are more likely to form network ties, thereby reducing the risk for the search of partners (Chung, Singh and Lee, 2000). Building on this, the following hypotheses suggest that geographical location enables organisations to obtain resources through distant interactions when significant differences exist between the organisations' resource complementarity.

Hypothesis on the interaction between complementary resources and geographical location (4): The effect of resource complementary positively moderates the relationship between geographical location and the propensity of organisations to collaborate.

6.2.4 Other factors: Collaboration network as an evolutionary process

In the existing literature on inter-organisational networks and economic geography, researchers have discussed about various factors that affect the network evolution related to how network structures emerge over time (Balland, Belso-Martínez and Morrison, 2016; Rivera, Soderstrom and Uzzi, 2010). On the basis of the literature, this study used four mechanisms, namely density, transitivity, and preferential attachment for network drivers to test for a social selection mechanism.

The first distinctive structural feature of inter-organisational networks is density and reciprocity (Rivera, Soderstrom and Uzzi, 2010). It also called the out-degree effect (Snijders, Van de Bunt and Steglich, 2010), i.e. the general tendency of organisations to establish new ties . It underlines how few organisations are responsible for a high number of ties, while most organisations have only a few ties (Powell *et al.*, 2005). Density captures the presence of social mechanisms that generate a greater variation in relational activities among organisations. It also refers to the cost associated with the establishment of relationships. Density may show the fact 'that organisations have limited capacity to start collaborations, which are time consuming, then the higher probability of ties redundancy' (Balland, 2012:19). Reciprocity describes the general tendency of organisations to reciprocate the existing network ties.

The second distinctive structural feature of inter-organisational networks is preferential attachment, i.e. the tendency to connect with other well-connected organisations (Rivera, Soderstrom and Uzzi, 2010). Barabási & Albert (1999) called this mechanism the 'rich get richer' effect, because older organisations may increase connectivity at the expense of younger ones. Organisations that have highly central and high-status actors receive an abnormal share of new network ties over time (Washington and Zajac, 2005). Because establishing and maintaining relationships is costly, this mechanism of tie formation may be associated with accumulative cost advantages.

The third distinctive structural feature of inter-organisational networks is clustering (Rowley, Baum, Shipilov, Greve, & Rao, 2004;Kogut & Walker, 2001). While it may be defined in a variety of ways, the general idea behind network clustering involves a tendency toward path

shortening at the organisational level: organisations connected to common third parties are more likely to become directly connected (Newman and Park, 2003), and in particular, have transitivity, i.e. the tendency of partners of partners to be partners. Path shortening is perhaps the mechanism of triadic closure that has been most commonly examined in the empirical studies on inter-organisational networks, as transitivity represents a dominant force underlying the creation of inter-organisational ties that are 'embedded in social attachments' (Uzzi & Lancaster, 2003:383). Path closure may be associated with situations wherein the sharing of multiple partners leads to a direct tie. The presence of transitive relationships may serve as a form of insurance against the disruption of resource flows and as a form of uncertainty reduction that may be adopted to facilitate access to multiple information sources. Empirical research on inter-organisational relationships conducted in the last thirty years has found rich evidence in support of this prescient conjecture (Lomi & Pallotti, 2013; Cropper, Ebers, Huxham, & Ring, 2008; Gulati & Gargiulo, 1999) .

6.3 Data and Variables

6.3.1 Setting

This study uses the network of collaborative patient transfer relations observed during a four-year period (2006-2009) between all the 110 hospitals providing health care services in Lazio – one of the largest Italian regions with a population of approximately 6ml inhabitants. Patient transfers is a particular form of inter-hospitals collaboration that has been examined in recent years in hospital care (Pallotti et al., 2015; Lee et al., 2011; Iwashyna and Courey, 2011; Iwashyna et al., 2009;). This study focuses in particular on the transfer of in-patients – that is, patients admitted into a (sender) hospital and later transferred to another (receiver) one under non-emergency conditions.

Because hospitals in this Region are not subjected to any institutional constraint as to when and where to transfer in-patients, a patient transfer relation as a voluntary arrangement between independent organizations to engage in joint problem-solving activities (Lomi and Pallotti, 2012). I treat the presence of patient transfer relations as an example of complex task that cannot exist without intense mutual exchange of resources channelled through network ties. Completing a transfer requires not only a complex coordination and information sharing

process between partner hospitals (Bosk et al., 2011) but also the combination of different sets of resources. In most cases, a transfer occurs when the sender hospital has not sufficient capacity to provide appropriate care.

Within each Italian region, responsibility for the organization and delivery of health services rests on geographically and population-defined institutions, the Local Health Units (LHUs). These administrative and territorial units depend directly on the regional government for financing. LHUs are under the direction of managers appointed by the regional government, and whose compensation is typically performance-related. LHU are responsible for the management of all health services in their area by providing care directly through their own facilities or through services supplied by hospital trusts, research hospitals and accredited private providers (acute and long-term hospitals, diagnostic laboratories, nursing homes, outpatient specialists and GPs). Patients are free to seek health care from any health care provider located within or outside their LHU of residence. Patients are also free to choose hospitals located in different regions.

The Lazio region is partitioned into 12 LHUs, with 8 LHUs concentrated in the capital city (Rome) and 4 LHUs covering the area of the other four provinces of the Region (Rieti, Latina, Viterbo and Frosinone). Most LHUs cover a population of approximately 500,000 inhabitants, with only 3 LHUs being responsible for the provision of services to less than 300,000 residents. LHUs in Lazio have been designed to be relatively self-contained, i.e., to be able to provide a wide range of care services to their target patient population.

I use the 12 LHU in the region to investigate spatial heterogeneity – while controlling for the geographical distance, because LHUs may be considered as important sources of spatial heterogeneity in at least three ways. First, each LHU is managed by a board of directors who may differ in strategic orientation and decision making from the board of directors of other LHUs. Second, human, financial and technological resources are unevenly distributed across the Region, where some LHUs are served by a higher number of health care providers which also differ in terms of material and human resources (Fabbri and Robone, 2010). Finally, a higher concentration of major hospitals (i.e., university policlinics and hospital trusts) in the capital city area (or urban area), and a more dispersed distribution of smaller hospitals in the periphery (i.e. rural area) are also important sources of spatial heterogeneity organized along the LHUs boundaries.

I choose resource complementarity, i.e. depth and scope and the LHU to investigate spatial and resource heterogeneity of social selection and influence processes. The analysis relies primarily on information contained in public records maintained in the Regional Hospital Information System database (SIO), which is managed by the Public Health Agency of Lazio (Agenzia di Sanita' Pubblica, ASP). This is a large administrative dataset, containing a wide range of information on hospitals and their activity, including a number of performance indicators.

6.3.2. Data

The dataset is the result of a 3-wave network panel design covering the period 2006–2010. We collected information on dyadic relations defined in terms of patient transfers among all the 110 hospitals operating in the region. The first two waves contain 110 hospitals, the third wave 107 hospitals, the fourth wave 103 hospitals.

Based on the information of SIO, the one-mode network was created and specify the external portfolio of network partners, i.e., how individual hospitals have established, maintained and dropped a collaboration via patient transfer relations. The four patient transfer matrices are asymmetric because for any hospital in the sample the number of patients sent differs from the number of patients received. The four patient transfer matrices have been dichotomized by using the row specific average values as threshold (Lomi, Pallotti and Zappa, 2018). This dichotomization considers hospital size, i.e. smaller (larger) hospitals might have less (more) capacity to manage larger networks of patients. Table 23 reports the descriptive statistics for the observed networks across the four waves. The first row reports the densities of the networks – i.e. the actual number of relations relative to the total number of possible relations – tend to remain stable over time and fluctuates around 0.04. The second row reports the average degree over the years that is 4.969 with small variation over the years. The average degree suggests that hospitals transfer on average five patients over the years.

Table 23: Descriptive network statistics over the years

	2006	**2007**	**2008**	**2009**
Density	0.045	0.045	0.046	0.046
Average degree	4.882	4.909	4.969	5.032

Number of ties	537	540	517	485
The average degree is 4.969				

Table 24 reports information on tie changes over the years. In the table, 0→0 (null dyads) indicates the number of hospitals that do not collaborate across the four time periods, whereas 1→1 indicates the number of hospitals that collaborate across the four time periods. The other two points (0→1 and 1→0) indicate the number of new collaborations and the number of dissolved collaborations over time periods respectively. Over the years, 430 new collaborations were created, and 460 existing collaborations dropped. The stability of the patient transfer networks over time is measured by Jaccard coefficients. The Jaccard coefficient range between 0 – if all ties changes- and 1 – if all ties remain the same (Snijders, Van de Bunt and Steglich, 2010). The stability of the patient transfer networks is a bit high ranging between 0.55 and 0.57 as shown in the table 24.

Table 24: Evolution of tie changes over years

T periods	0→0	0→1	1→0	1→1	Jaccard coefficient
1→2	11295	158	155	382	0.550
2→3	10661	147	164	370	0.543
3→4	9880	126	141	359	0.573

6.3.2 Variables

To assess the relative importance of complementarity resources and spatial location on the formation and evolution of inter-organisational collaboration networks, the empirical model specification includes structural and attributional factors. Regarding the attributional factors,

two type of covariates are used, such as monadic and dyadic. Monadic are defined at the organisational level while dyadic covariates refers to hospitals dyads.

Dyadic covariate

Geographical distance. Geographical distance is measured as distance in kilometres between each pair of hospitals. This variable controls for the tendencies of hospitals to exchange patients to more proximate partners. It is time independent and its values do not change over time.

Scope complementarity. To test for scope complementarity in the typology of clinical services held by hospitals and offered to patients (i.e. number of clinical wards related to overlapping specialties), I reconstructed four 2-mode binary matrices of hospitals by clinical specialties they contain. I computed the Euclidean Distance between hospitals spanned by all the clinical specialties. Hospitals that are farther away from each other offer potentially complementary services and are more likely to exchange patients. Hospitals, hence, that exhibit high level of scope complementarity are more likely to be selected and hence to collaborate.

Depth complementarity. To test for depth complementarity in the distribution of distribution of resources, hospital beds allocated to the various clinical specialties, I reconstructed four 2-mode matrices of hospitals by clinical specialties (i.e. number of hospital beds related to clinical specialties). I dichotomized the four 2-mode weight matrices of hospital by hospital beds they contain. computed the Jaccard coefficients between hospitals spanned by all hospital beds allocated to the various clinical specialties. Hospitals that exhibit high level of depth complementarity are more likely to be selected and hence to collaborate.

Monadic covariate

The reaming organisation-monadic covariates enter the empirical model specification as sender and receiver effects to control for additional factors that may affect the formation of network ties.

Number of beds. It is measured as the total number of hospital beds set up and staffed for use in hospitals. The number of beds controls for the effects of size on the propensity of hospitals to exchange patients.

Organisational form. This variable captures the institutional diversity of hospitals in the region and reflects the official classification adopted by national health authorities. It is a categorical

variable ranging from 1 to 6. Each institutional categories reflect the differences in normative, organisational constraints and in ownership- governance structure operating on hospitals. The boundaries of these institutional categories reflect fundamental differences in normative and organisational constraints operating on hospitals, as well as broad differences in forms of ownership and governance.

Geographical location. This variable captures the geographical location of each hospitals assigning to its reference LHU. This is categorical variable ranging from 1 to 12. This variable controls the effect that location in the same (different) LHU encourages the establishment of new collaboration between hospitals.

Occupancy rate. It is defined as the ratio of occupied beds to the total of available beds. It is included to capture the ability of hospital management to allocate internal capacity. High occupancy rates means that hospitals are better able to manage its capacity (i.e. the closer the hospital is to 1). It is considered as a measure of operational performance. This variable represents the behavioural variable of interest in this study. The occupancy rate is a continuous variables taking values in the interval (0,1). SAOMs are currently implemented for ordinal behaviour and therefore the occupancy rate was categorised into 4 categories using intervals equals to the quartile of the distributions.

Readmission rate. It is defined as the percentage of patients treated who are readmitted in the same hospitals for the same pathology within 30 days from discharge. It is included to capture the quality of treatment offered by hospitals. It is considered as a measure of clinical performance.

Table 25 summarizes the descriptive statistics and definition of all variables included in the empirical model specification.

Table 25: Organisational specific variables

VARIABLE	**DESCRIPTION**	**RANGE**	**MEAN**	**ST.DEV**
Geographical location –LHU- (*monadic*)	Administrative and geographical units	From 1 to 12	-	-

Organisational form- org.form – (*monadic*)	Type of ownership-governance structure	1-6	-	-
Occupancy rate-occ.rate – (*monadic*)	Proportion of beds occupied	1-4	3.482	0.892
Readmission rate -read.rate – (*monadic*)	Percentage of patients treated who are readmitted in the same hospital for the same pathology	0-0.328	0.028	0.035
Size - n.beds – (monadic)	Number of beds	3-1906	205.9	271.503
Depth complementarity – depth.compl- (*dyadic*)	The distribution of resources hospital beds allocated to the various clinical specialties	0-14	8.631	1.881
Scope complementarity-scope.compl. (*dyadic*)	The range of services-Clinical specialties hold by hospitals	0-10	7.725	1.995
Geographical distance- geo.dist. – (*dyadic*)	Distance in kilometres	0.002 – 222.60	49.780	40.261

	between every pairs of hospitals			

6.4 Methods

Stochastic Actor Oriented model for network dynamics – SAOM

Snijders (1996, 2001) proposes Stochastic Actor Oriented model (SAOM) to study the coevolution of network structure and individual behaviour. To account for process of collaboration and network selection and influence, this paper uses SAOMs that allows to specify the network selection and influence processes as a function of actors' attributes, while controlling for network structural process on the formation and evolution of inter-organisational networks (Snijders, Van de Bunt and Steglich, 2010). In this study, the model allows to separate the impact of resources complementarity, i.e., scope complementarity and depth complementarity and geographical location (and the joint effect of them and geographical distance) – from network structural mechanisms (i.e. reciprocity, density, transitivity and preferential attachment) contribute to partner selection and influence and inter-organisational collaboration network dynamics.

SAOMs are based on several assumptions that are important to model network formation. First, SAOMs view actors in the network as agent that make choices about their outgoing ties, i.e. a discrete series of choices typically interpreted as driven such as social preferences (Snijders, Van de Bunt and Steglich, 2010). In this view, relationships are considered in terms as enduring states, thus is consistent with conceptualization of collaboration relationships. Second, the models assumes that network continuously change, happening between two time points, and thus follows a Markov process: the next state of the chain is probabilistically affected by the current state. During each single moment, an actor could be selected and has the opportunity to maintain or drop relationships one at a time. In SOAMs actors in a network may be thought of decision-makers. In other words, actors have the possibility for a network change that is the creation of a new outgoing relationship, termination of an existing relationship or do nothing. This is done by using the rate function which also permits for parameters to be modelled to represent the endogenous network effects. The model also allows to distinguish between ego or sender (actor who selects a partner) alter or receiver (actor who is being selected); and the

similarity effect measures whether ties tend to occur more often between actors with similar values on a given attribute (i.e. homophily effect). Finally, SAOMs posit that actors know the other members in the network.

To account for the process of complementarity resources and spatial location on the formation and evolution of inter-organisational collaboration networks, this study uses R-based Simulation Investigation for Empirical Network Analysis (RSiena).

Table 26 describes the structural effects that are used in the empirical model specifications.

Table 26: Structural effects

Effect	Description
Out-degree (density)	It shows the preference to establish ties
Reciprocity	It shows the preference to reciprocate relations
Transitivity (transitive triplet)	It shows the preference to establish relationships to the partners of one's partner
Preferential attachment (out-degree popularity – square root)	It shows the preference to establish ties with other actors that are well connected

6.5 Results of Siena analysis

The aim of this study was to explore the effect of complementarity by adding a geographical component to the investigation of the dynamics of inter-organisational collaborative networks. The results presented in Table 5 revealed that the effect of resources complementarity is contingent on the geographical location of hospital organisations. I will subsequently elaborate on these results and discuss the rate parameter.

The rate parameter is reported in Table 27 and shows the frequency at which a network change-explains the opportunity for organisations to form, maintain, and drop ties between the time periods observed.

Table 27: Results of RSiena estimation - (Standard errors in parentheses)

Social selection model

Rate parameter period 1	3.1627 (0.2697)
Rate parameter period 2	3.7654 (0.3238)
Rate parameter period 3	3.9060 (0.3241)
Out-degree	-2.355*** (0.155)
Transitive triplets	0.244*** (0.024)
Out-degree popularity	0.292*** (0.084)
Reciprocity	0.821*** (0.143)
Scope complementarity	0.014 (0.031)
Depth complementarity	0.030* (0.017)
Geographical distance	-0.010*** (0.002)
Same Organizational form	0.044 (0.099)
Same LHU	0.869*** (0.098)
Same LHU*Scope	0.078 (0.049)
Same LHU*Depth	0.069** (0.027)
Occupancy rate (Ego)	0.372*** (0.106)
Occupancy rate (Alter)	0.193* (0.097)
Occupancy rate (Similarity)	0.054 (0.280)
Readmission rate (Ego)	0.427*** (0.126)
Readmission rate (Alter)	0.314** (0.120)
Readmission rate (Similarity)	0.722* (0.360)

Size (Ego)	0.000*	(0.000)
Size (Alter)	0.001***	(0.000)

All convergence t ratios < 0.06. Overall maximum convergence is 0.09.
Legend: * p<0.05; ** p<0.01; *** p<0.001

Social influence model

Occupancy rate period 1	3.008	(0.873)
Occupancy rate period 2	1.049	(0.242)
Occupancy rate period 3	2.716	(0.672)
Occupancy rate linear shape	0.766*	(0.303)
Occupancy rate quadratic shape	0.686*	(0.140)
Occupancy rate average similarity	6.609**	(2.348)

All convergence t ratios < 0.05. Overall maximum convergence is 0.17.
Legend: * p<0.05; ** p<0.01; *** p<0.001

I consider parameters in the network evaluation function indicating which effects are responsible for tie changes. All the structural (i.e., endogenous) effects are significant. The negative density parameter (out-degree) is the direct consequence of low network density. According to a strict utility interpretation, this means that, on average, the benefit of creating a tie may be lower than its cost. The parameter associated with reciprocity is positive, and therefore if hospital i receives patients from hospital j, it is more likely that hospital i will be transferring patients to the hospital j. The parameter associated with transitivity is positive and therefore, suggests that the presence of indirect ties improves the chance of forming a new relationship. In other words, if hospital *i* considers j and h as partners, hospital j will be more likely to establish a collaborative relationship with hospital h in the future. The parameter associated with preferential attachment (out-degree popularity) is positive and significant, indicating that the propensity to send patients to popular hospitals is higher. This in turn suggests that hospitals that are popular (because they are selected by many other hospitals as partners) are likely to become even more popular in the future.

Resources complementarity affect patient transfers in an interesting way: on one hand, the positive parameter of depth reveals clear tendencies of hospitals to select partners that offer

high level of depth resource. This confirms Hypothesis 2. On the other hand, the insignificant parameter associated with the scope complementarity suggests that there is no evidence of a preference of hospitals for transferring patients to hospitals that offer scope complementarity.This does not support Hypothesis 1.

Predictably, geographical distance has a negative effect on patient transfer. The negative parameter implies that hospitals may be reluctant to transfer patients across long distances (this supports Hypothesis 3). A similar effect contributing to make patient transfer ties more localized is associated to membership in the same LHU. The corresponding parameter shows a preference of forming ties between hospitals located in the same LHU. The positive and significant parameter for the interaction effect between depth complementarity and same LHU, suggests that even if hospitals are geographically dispersed the preference to collaborate is higher when they have similar resources-type. Sizes of the sender and receiver hospitals are also significant and positive, indicating that there is a preference to form ties with larger hospitals. Finally, there is not a preference of hospitals to form ties with hospitals that have the same institutional and governance structure (organizational form).

The last three effects of the network evaluation function model social selection based on the occupancy rate and readmission rate. Regarding the occupancy rate, the occupancy rate of the sender and receiver hospitals are significant and positive suggesting that there is a preference of hospitals to transfer patients to partners with a high occupancy rate, i.e., to hospitals that are better able to manage their internal capacity. However, operational performance is not a significant basis of homophily for the hospitals in my sample. Regarding the readmission rate, the readmission rate of the sender and receiver hospitals are significant and positive suggesting that hospitals tend to transfer patients to other hospitals that are better able to treat these patients. The fact that hospitals tend to preferentially select partners hospitals of similar quality may be interpreted as the evidence of homophily.

I consider now the estimated behavior evaluation. The parameters of the quadratic and linear shape effects are interpreted jointly. In my case the quadratic shape effect is positive suggesting that hospitals prefer behavioral values close to the mean value. The positive parameter associated to the average similarity effect, suggests the presence of a diffusion process that tends to make the operational performance of hospitals progressively more similar to the average operational performance of their partners. This result may be interpreted as an evidence

of the fact that collaboration induced by resources complementarity does affect organizational performance.

6.6 Discussion and Conclusion

This study aims to explore the effect of resources complementarity by adding a geographical component to the study of the dynamics of inter-organisational networks. More specifically, I propose a new analytical methods that allows to explore the degree to which two main mechanisms underlying the evolution of networks (i.e social selection and social influence) are spatially heterogeneous, i.e. the effect of resources complementarity differentially affect group of organisations located in different geographic areas.

In doing so, this study pursued two main contributions. The first was to answer the call made by Furlotti & Soda (2018) and Soda & Furlotti (2017) to study complementarity as the determinants of network structure, the consequences of network structures and how these structures change over time. Complementarity exchange is required to ensure the execution of a given task (Soda and Furlotti, 2017). Second, previous research has highlighted the relevance of physical location when examining network ties among organisations. In general, collaborative relations are expected to exist between organisations that are complementary and proximate. Physical location is a source of heterogeneity in organisational field.

More specifically, I drew three main conclusion from the results of the present study. First, I found showed that depth complementarity had a positive effect on the creation of collaborative ties, while scope complementarity did not affect the creation of collaborative ties. This results confirmed the findings of other empirical studies where " the quality of inter-organisational matches may depend on the possession by the actors of resources of the same kind" (Soda and Furlotti, 2018: 23). Second, by adding physical location to resource complementarity, the outcome reveals that the effect of resources complementarity is contingent on the geographical location of hospital organisations. This means that complementary hospitals preference to create ties if located to the same geographical areas. It could be supposed that proximity plays a subordinate role in urban areas, since are more hospitals in urban areas. Finally, I found that collaboration induced by resources complementarity affect organisational performance. More specifically, hospitals assimilate their individual level of capacity management to the average level of their partners whereby hospitals with more effective partners tend to emulate them and hence become more similar.

The second contribution was to propose SOAMs as statistical model to investigate resource complementarity and geographical location on the co-evolution of inter-organisational networks and organisational behaviour. To the best of my knowledge, this is the only paper that has used SOAMs to address issues of resources complementarity and spatial heterogeneity.

6.6.1 Limitation and Future work

This study suffers from a number of limitations that reduce the possibility of empirical generalization, but – at the same time- invite future research. The first limitation is related to the fact that healthcare sector is undoubtedly only one sector and it has a number of unique institutional and social features. However, hospitals are not the only members of the organisational world and as in most field studies organisational context puts boundaries on result interpretation. For these varied reasons, the results cannot be generalized. Only the replication in other settings of the effects that the models have revealed might give a better understanding of the social mechanisms underlying the complexity of selection between organisations.

The second limitation is related to the fact that this study has analysed only one specific form of relation. While different studies have acknowledged the fact that this relation captures an important dimension of collaboration between hospitals (Lomi & Pallotti, 2013, 2012), hospitals can collaborate in other ways, such as an exchange of doctors, cross training of medical staff and technology transfer. Future studies will have to pay attention to the multiplexity that inter-organisational collaboration is likely to involve (Lomi and Pattison, 2006).

The third limitation is related to the data. the scope of this study. This study used only one-mode network (hospital to hospital network), recently studies have emphasized the multilevel nature of organisations characterized by two interconnected levels, such as micro level -defined in terms of affiliation of hospitals to activities-, and macro level- defined in terms of relation of hospitals to hospitals (Amati *et al.*, 2019; Stadtfeld *et al.*, 2016). Future research could use bipartite networks to better understand how individual heterogeneity frames the contextual meaning of the social selection process in organisational communities.

Chapter 7: Conclusion

The network approach is a distinctive lens that brings into the examination the relational nature of the organisations. Organisations do not operate in isolation but are embedded in a web of relationships that provide opportunities and place behavioural constraints. Therefore, studies on these organisations will not be effective without considering the broader structured pattern of the relationships influencing organisational behaviour. The main aim of this dissertation was to explore the multifaceted concept of similarity in the study of organisational behaviour at an inter-organisational level over time. Using the inter-organisational network framework, this dissertation looked at how the different dimensions of similarity, i.e. output, social space, and multiform dynamics, interacted and affected the inter-organisational network structures and the organisational behaviour.

The review of the existing literature allowed the identification of the gaps and led to the main research questions of this dissertation: *What makes collaboration and coordination among organisations more likely to occur? What are the effects of collaboration and coordination on organisational behaviour and performance?* This dissertation addressed the gaps in the existing literature on inter-organisational, where organisations became progressively more similar in their behavioural orientation and outcomes over time. It presented three empirical studies that mapped the association of organisations and the network theory to study the dynamics of inter-organisational networks. It overcame the issues of inter-organisational network scholars with respect to the distinct social processes of social influence and social selection and how these affected network structures and organisational outcomes, by using the concepts of similarity and complementarity. More specifically, the first empirical study (Chapter 4) looked at similarity as an output by using the concept of peer effects. It showed how peer effects influence organisational performance and foster performance similarity at three different network levels. The second empirical study (Chapter 5) looked at similarity as the social space by using the concept of social similarity. It showed how social similarity moderated the effect of geographical proximity. The third empirical study (Chapter 6) looked at similarity as a multiform dynamic by using the concept of resources complementarity. It showed how resources complementarity is contingent on the geographical location of organisations.

The results of all the empirical studies were robust, and post hoc analyses were performed. With the use of a longitudinal design, the problem of the change in the inter-organisational network was considered, and the generalised method of moments (Chapters 4 and 5) and the stochastic actor-based model (Chapter 6) were applied. Empirically speaking, this dissertation used the healthcare sector as the setting and used the data on patient transfers to illustrate how inter-hospital patient networks were formed and maintained.

7.1 Contribution

In this dissertation, I sought to expand the use of network analysis in inter-organisational literature in several ways. Firstly, it contributes to the existing theoretical knowledge by specifying the processes and mechanisms through which similarity affects the social network dynamics, thus responding to the calls to study how organisational actions contribute to the formation and the dissolution of the social structure over time (Knoben, Oerlemans and Rutten, 2006). Secondly, it contributes to the understanding of the link between organisation-level actions and how these are affected by the network, which is crucial for theorising the evolution of inter-organisational networks that are a result of the micro-dynamics of the organisations, such as partner selection and peer influence. Thus, this dissertation advances the understanding on SNA theory in three areas of on-going inquiry, namely network theory, theory of networks, and network theory of networks (Borgatti and Halgin, 2011). This dissertation uses a longitudinal design to investigate how and why inter-organisational networks evolve, thus responding to the calls to use a longitudinal framework to explore the dynamics of inter-organisational networks (Valente and Pitts, 2017). Finally, this dissertation uses the inter-hospital network of patient transfers, while a majority of the existing work focuses on inter-physician networks.

More specifically, the contribution of each of the empirical studies is elaborated upon below.

Empirical study 1

The first empirical study used the concept of peer effects as a framework for exploring the performance consequences of inter-organisational relationships. More specifically, the study compared and adjudicated among various competing levels, i.e. the related mechanisms that might be responsible for observing performance similarities among connected organisations. It examined three alternative mechanisms capable of sustaining this prediction: (i) Organisations were more likely to perform similarly at the dyadic level, where the relational mechanisms

involved only one organisation and its immediate partners. (ii) Organisations were more likely to perform similarly in network subgroups, where the cohesion mechanism of clique co-membership in overlapping cliques involved a mid-range influence of the network subgroup. (iii) Organisations were more likely to perform similarly at the network level on the whole, where the positional mechanism of structural equivalence involved a global range of the network into positions. The aim of this study was to investigate at which of these levels did the inter-organisational peer effects operate to increase the inter-organisational performance similarities among the connected organisations. The empirical analysis of dyadic performance similarities between hospitals supported the following conclusions: (i) Direct network ties and their strength in increasing the performance similarity. However, the strength of the direct ties increased the performance similarity up to a certain point; after this point was reached, the performance similarity started to reduce. (ii) Organisations occupying similar network positions increased the performance similarity up to a certain point; after this point was reached, the performance similarity started to reduce. (iii) Clique co-membership in the network subgroup did not necessarily increase the performance similarity. The results contributed to understanding that the effects of inter-organisational peers on the inter-organisational performance similarities varied with respect to the specification of network boundaries. This answered to the call made by Pallotti, Tubaro, & Lomi (2015) and Mizruchi & Marquis, (2006) to study the joint effects of the network levels on the behaviour similarity (i.e. peer effects) among organisations. These results also contributed to forming a bridge between two different research fields: inter-organisational networks and economics.

Empirical study 2

The second empirical study used the concept of social similarity as a framework for exploring the formation of inter-organisational relationships. More specifically, the study tested the conjecture that the effect of geographical proximity (i.e. distance in a physical space) on the formation of collaborative network ties among the organisations was moderated by the effect of social similarity (i.e. distance in the positions that organisations occupied in a relational space). It examined how the negative effect of geographical distance on inter-organisational collaboration decreased with an increase in the social similarity. The aim of this study was to investigate the joint effect of geographical proximity and social similarity on the formation of collaborative ties between organisations. The empirical analysis of the strength of the dyadic collaboration between hospitals supported the following conclusion: the negative effect of

geographical distance decreased with an increase in the similarity of the network position. These results contributed to the understanding of the joint effects of geographical proximity and social similarity on the formation of network ties. This study also contributed to the call made by Knoben & Oerlemans (2006) to reduce the conceptual ambiguity around the different forms of proximity, i.e. social similarity. To theoretically test social similarity, this study proposed a measure that went beyond the dyadic level and emphasised its positional dimension. The proposed measure looked at social similarity from the perspective of the network positions that organisations came to occupy within the social network structures.

Empirical study 3

The third empirical study used the concept of complementarity as a framework for exploring the formation of inter-organisational relationships. More specifically, the study tested how complementary resources (i.e. scope and depth complementarities) contributed to the formation of collaboration network dynamics, when geographical location was also taken into account. It examined the degree to which the social selection was spatially heterogeneous, i.e. how complementary partners affected the groups of organisations located in different geographic areas. The aim of this study was to explore the interplay between complementarity and physical space by adding a geographical component to investigate the dynamics of inter-organisational collaborative networks. The empirical analysis of this study supported the following conclusions: the effect of complementarity on the propensity to collaborate varied consistently across the geographical location of organisations. The results contributed to the understanding of one of the main mechanisms underlying the evolution of networks, i.e. social selection. This study contributed to the call made by Furlotti & Soda (2018), Soda & Furlotti (2017) to test the effect of resource complementarity on the evolution of inter-organisational networks. This study also contributed to the call made by Ter Wal & Boschma, (2009) to study the determinants of network structures and how structural and exogenous factors affected the evolution of inter-organisational networks in space.

Table 28 shows the theoretical contributions of the empirical studies.

Table 28: Theoretical contributions of the empirical studies

Empirical study	Research question	Theoretical contribution
Study 1	At what levels are peer effects more likely to operate?	It contributes to understand the joint effects of network levels on behaviour similarity i.e. peer effect. It integrates two different streams of research: inter-organisational networks and economics and examining the impact of peer effects on inter-organisational performance similarity at three different network levels
Study 2	What is the joint effect of geographic proximity and social similarity on the formation of collaborative network ties among organisations?	It contributes to two different streams of researches: inter-organisational networks and economic geography and examining how the position of organisations in both physical and network spaces interact to affect patterns of collaboration among organisations. It introduces a measure of social similarity that is positional rather than relational
Study 3	How do resources complementarity affect the selection of collaborative partners and how these affect organisational performance?	It contribute to understand the role of complementarity and geographical location on the evolution of inter-organisational collaborative networks

7.2 Limitations and future research

While the questions on the circumstances in which organisations are more likely to behave similarly can be answered by conceptualising the multifaceted dimensions of similarity in the formation and the endurance of collaborative network ties among hospital organisations, there are a few limitations that need to be acknowledged.

The first is the context of the dissertation which needs to be considered. Hospitals can be considered to be only a sample of organisations with strong institutional factors. In the institutional context, network structures could vary across different settings depending on the institutional norms and the varying levels of connectedness of the inter-hospital networks. A

comparative analysis could provide further insights into the evolution and the outcomes of collaborative networks. Second, this dissertation uses patient transfer relationships to understand the circumstances under which hospital organisations collaborate, and this has been acknowledged in the existing literature. However, it needs to be acknowledged that there are several other forms of collaboration that hospital organisations are engaged in, such as sharing physicians, cross training of medical staff, and technology transfers. Future research could pay attention to all of these forms of collaboration and use the statistical models that this dissertation proposed to see which of these forms of collaboration are more effective for hospital organisations to guarantee the continuum of care.

7.3 Managerial and policy implications

Despite these limitations, the findings in this dissertation have important implications for managers and policymakers in the Italian context. Using the relational lens, we can look at the healthcare system as a network of interactions among healthcare providers. It has been argued that hospitals are embedded in a collaborative network relations through patient transfers, therefore this dissertation incentives hospital managers to include social network analysis as technique to understand the current situation about their collaborative networks and improve the quality of care and patients experience. Specifically, when discussing peer influence, I identified how hospitals can assimilate the performance of their peers depending on how they are embedded within the network. The findings of the first study allows hospital managers to make strategic decisions based on the ability to structure their network in terms of with whom they are connected to- in order to improve hospital performance. For policy makers, this underlines the importance of accounting for broad patterns of relationships when policies are oriented to influence coordination and variation in the quality of care. These patterns of relationships may also influence an individual hospital's ability to respond to policy initiatives quickly and efficiently.

These patterns of relationships among hospitals were identified by using patient transfers as a form of collaboration among hospitals. It has been argued that the healthcare system is characterised by two interrelated forces: competition and collaboration. This is particularly true for the Italian healthcare system where the introduction of decentralisation and managerialism has progressively increased the competition among providers to attract more patients and collaborate in order to provide a continuum in the delivery of healthcare services. Therefore, the spatial identification of the pattern of collaboration has important implications for

understanding the competitive pressure. Because these network structures are associated with the intensity of patient flow, a variation in these structures caused by competition could form a part of the explanation for the previously unexplained agreements between hospitals. For instance, I found that proximate partners facilitate the formation of collaborative ties across short distance, but also that partners that are directly and indirectly connected through patient transfers are more likely to collaborate across geographical boundaries. Therefore, the result of study 2 can be useful for hospital managers who want to adjust their behaviour, i.e. hospital managers can take better decision in planning and organising healthcare delivery networks by identifying socially and geographically proximate partner. Hospitals that are already socially proximate are likely to have stable and trusted partnership which can be used as starting point for future collaboration. For policy makers, this point highlights the importance of considering incentives for inter-hospital collaboration through new regulations aimed at improving their financial efficiency. This will improve the efficiency of services provided to the patients, thereby suggesting that hospitals would benefit from policies that facilitate collaboration.

The final key policy implication of this research is that hospitals appear to select partners depending on whether these organisations hold resources complementary and are located in different geographical areas. This finding is important because of the recent concern regarding how hospital managers manage the hospital costs and resources. It shows a significant contribution to policy, which will help hospitals to make strategic choices on the basis of their ability to structure their networks and to identify and exploit the knowledge held by capable partners. The identification of which resources to obtain and where to get them enables managers to understand opportunities and benefit from collaborative relationships. For managers, this point stresses the importance of taking into account resources that potential partners will be willing to contribute for a future collaboration. The fact that resources make an organisation a more attractive alliance partner can reduce the search for partners and decrease costs. Managers can evaluate their collaboration for achieving strategic goals through the pooling of observable resources.

In summation, this dissertation represents a substantial step forward in the understanding of the healthcare system as a network of relationships among interdependent hospitals collaborating with each other for their mutual benefits. Gaining an understanding of the network may lead to the consideration of new interventions into the delivery of healthcare services in order to achieve a high-performing healthcare system.

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Appendix A

Hierarchical model

I repeated the analysis by following a hierarchical order from the simple to a complex models (including the all variables) in order to understand the difference between the longitudinal and cross-sectional results. The variable clique co-membership is not significant across models, while the variable direct ties (strength) becomes negative significant in the model M10- M13-M14-M15-M16-M17; and the variable structural equivalence is always negative significant as a well the binary variable Direct tie .

M0= tie strength

M1= M0+ direct tie

M2= M1+ Clique co-membership

M3= M2+ Structural equivalence

M4 = M3+ squared variable of direct ties

M5= M4+ squared variable of Clique co-membership

M6= M5+ squared variable of structural equivalence

M7= M6+ geographic distance

M8= M7+ Competitive interdependence

M9=M8+ Complementarity

M10=M9+ Number of beds (diff.)

M11=M10+ Number of discharges (diff.)

M12= M11+ Surgical DRG (diff.)

M13=M12+ LHU (matches)

M14=M13+ Organisational form (matches)

M15=M14+Urban non Urban receiver effects

M16=M15+ level of care (matches)

M17= M16+both disconnected (matches)

Table 1. Estimate of different models - Multiple regression results estimated by GMM

Variable	**M0**	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**
Lagged CPI (diff.)	.85363968***	.84940224***	.84952876***	.84548104***	.84542414***	.84534976***	.84090725***	.83802815***
Direct tie		.03982746***	-.0385917***	-.0320375***	-.03087908***	-.03018846***	-.02686473***	-.03006501***
Tie strength	-.00045599	.00001108	.00002457	.00005632	-.00022244	-.00021115	-.00021803	-.00030138
Clique co-membership			-.00040083	-.00016879	-.00013604	.00057914	.00028674	-.00054702
Structural equivalence				-.10432263***	-.1038605***	-.10348941***	-.26557715***	-.31039817***
Squared variable of direct ties					1.262e-06	1.226e-06	1.256e-06	1.455e-06*
Squared variable of Clique co-membership						9.813e-06	7.451e-06	9.701e-06

Squared variable of Structural equivalence							.30035416***	.3452912***
Geographic distance								-.00031847**
Competitive interdependence								
Complementarity								
Number of beds (diff.)								
Number of discharges (diff.)								
Surgical DRG (diff.)								
LHU (matches)								
Organisational form (matches)								
Urban non Urban receiver effects								
Level of care (matches)								
Both disconnected (matches)								
_Itime2	-.02218721	-.02158152	-.02155477					
_Itime 3				.02121511	.02121936	.02121509	.02085037	.02047347
_Itime 4	.04128919*	.04155721*	.04152186*	.06294103**	.06295713**	.06294584**	.06313656**	.06304879**
_cons	.07524223***	.08311093***	.08310271***	.06862164***	.06865089***	.06867824***	.07346046***	.09350329***

Variable	**M8**	**M9**	**M10**	**M11**	**M12**	**M13**	**M14**
Lagged CPI (diff.)	.83045175***	83053066***	.82961796***	.82906053***	.82928636***	.82967294***	.82665017***
Direct tie	-.03195635***	-.03150022***	-.03195694***	-.03266023***	-.03255807***	-.03289348***	-.03328403***
Tie strength	-.00032819	-.00031938	-.00039953*	-.00036695	-.00036517	-.00042538*	-.00042712*
Clique co-membership	.00038974	.00039844	.00022641	-.00003262	-7.918e-06	.00001307	-5.482e-06
Structural equivalence	-.31100992***	-.31031012***	-.30062421***	-.3033619***	-.30172308***	-.30264685***	-.31213143***
Squared variable of direct ties	1.379e-06*	1.353e-06*	1.538e-06*	1.390e-06	1.385e-06	1.571e-06*	1.590e-06*
Squared variable of clique co-membership	2.693e-06	2.569e-06	3.435e-06	6.628e-06	6.412e-06	6.567e-06	6.895e-06
Squared variable of structural equivalence	.33708904***	.3353199***	.32608706***	.32880417***	.32655264***	.32036629***	.32659405***
Geographic distance	-.00057965**	-.00057916**	-.00055629**	-.00056882**	-.00056813**	-.00055047**	-.00057324**
Competitive interdependence	-.11930699	-.00088533	-.11747141	-.1166593	-.11730791	-.11715455	-.11533564
Complementarity		-.00088533	-.00979051*	-.0081833	-.00803658	-.00795536	-.00675705
Number of beds (diff.)			.00004297*	.00008054**	.00008045**	.0000804**	.00008191**
Number of discharges (diff.)				-7.745e-07*	-7.779e-07*	-7.751e-07*	-7.565e-07*
Surgical DRG (diff.)					.00339176	.00326186	.00554593
LHU (matches)						.01027144	.00980606
Organisational form (matches)							.01613404***

Urban non Urban receiver effects							
Level of care (matches)							
Both disconnected (matches)							
_Itime2							
_Itime3	.02131296	.0213328	.02159726	.02148098	.02131013	.02125353	.02125411
_Itime4	.0618295**	.06190834**	.06220232**	.0621156**	.06187106**	.06180261**	.06164618**
cons	.1239126***	.12651141***	.14422512***	.14141049***	.13997891***	.13811916***	.13022843***

Variable	**M15**	**M16**	**M17**
Lagged CPI (diff.)	.82664725***	.82716602***	.82721403***
Direct tie	-.03327891***	-.03312943***	-.03310694***
Tie strength	-.00042656*	-.00042173*	-.00042209*
Clique co-membership	-7.915e-06	-.0000225	-.00002209
Structural equivalence	-.31217829***	-.31218272***	-.312367***
Squared variable of direct ties	1.590e-06*	1.595e-06*	1.596e-06*
Squared variable of clique co-membership	6.913e-06	6.907e-06	6.899e-06
Squared variable of structural equivalence	.32662989***	.32731392***	.32749861***
Geographic distance	-.00057352**	-.00057752**	-.00057853**
Competitive interdependence	-.11531021	-.11489021	-.11504813
Complementarity	-.00674964	-.0066697	-.00668301
Number of beds (diff.)	.00008191**	.0000815**	.00008151**
Number of discharges (diff.)	-7.570e-07*	-7.578e-07*	-7.578e-07*

Surgical DRG (diff.)	.00553477	.00524536	.00524793
LHU (matches)	.00979117	.00951786	.00946551
Organisational form (matches)	.0161348***	.0161513***	.01617861***
Urban non Urban receiver effects	-.00081615	-.00067926	-.00070736
Level of care (matches)		.00771192	.00774685
Both disconnected (matches)			-.13056905***
_Itime2	-.02125514	-.02110667	
_Itime3			.02112784
_Itime4	.04038802*	.04038148*	.0615056**
Cons	.15190062***	.14578608***	.12478114***

legend: *p<0.05; **p<0.01; ***p<0.001

Results of statistical tests (Wald tests) for empty (M0), linear (M3) and quadratic models (M4)

Table 2. Wald test results

Linear versus Empty	**Linear versus Quadratic**
(1) pexch = 0	(1) p = 0
(2) ccmemb = 0	(2) s = 0
(3) sequi = 0	(3) c = 0
(4) connect = 0	chi2(3) = 14.15
chi2(4) = 25.04	Prob > chi2 = 0.0027
Prob > chi2 = 0.0000	

.

Panel regression results

Table 3. Panel regression results

Variable	**P1_cluster**
Dependent Variable CPI diff	
Direct tie	**-.01524595**
Tie strength	**.00004014**
Clique co-membership	**-.00021793**
Structural equivalence	**-.12132634****
Competitive interdependence	-.47344912*
Complementarity	-.03566958
Number of beds (diff.)	.00022887**
Number of discharges (diff.)	1.431e-06
Surgical DRG (diff.)	-.03183042
Time 2	.02741529*
Time 3	06443509***
Time 4	.13302752***
Cons	.34954069**

Legend: *p<0.05; **p<0.01; ***p<0.001

Cross-section regressions results

Table 4. Cross-sectional regression results

Variable	**C2_cluster**
Dependent Variable CPI diff	
Direct tie	**-.12795859*** **
tie strength	**.00080489**
Clique co-membership	**-.0018369**
Structural equivalence	**-.42638088*** **
Competitive interdependence	-.2571774**
Complementarity	-.03151344**
Number of beds (diff.)	.00025431***
Number of discharges (diff.)	-2.483e-06***
Surgical DRG (diff.)	.06941218*
Urban non Urban receiver effects	-.00469469
Level of care (matches)	.02148153
Both disconnected (matches)	-.34421812***
Géographique distance	-.00140942***
Organisational form (matches)	.02619065**
LHU (matches)	.05321158**
Cons	.53850685***

Legend: *p<0.05; **p<0.01; ***p<0.001

Appendix B

1. Dynamic panel with count data : Model with linear feedback

Variable	M1	M2	M3	M4
L.pexch	0.7154***	0.7146***	0.7147***	0.71***
s.e.	0.146	0.146	0.146	0.147
cent_bS	0.0012***	0.0011***	0.0012***	0.0013**
s.e.	0.000	0.000	0.000	0.000
cent_bR	0.0013***	0.0013***	0.0013***	0.0011***
s.e.	0.000	0.000	0.000	0.000
cent_gd	-0.0212***	-0.0185***	-0.0193***	-0.0257***
s.e.	0.003	0.004	0.004	0.007
b0	-1.5371**	-1.5583**	-1.5621**	-1.2617*
s.e.	0.513	0.501	0.504	0.498
cent_sequi		1.8421***	2.6167***	1.8915***
s.e.		0.482	0.279	0.359
inter_cent_gd_sequi			0.0283**	0.0362*
s.e.			0.01	0.014
cent_rrS				-4.296
s.e.				4.549
cent_rrR				-1.6477
s.e.				2.107
cent_surgS				-0.7272
s.e.				0.571
cent_surgR				-1.5749**
s.e.				0.497
rmnnrm_s				-0.7954
s.e.				0.511
rmnnrm_r				-0.5311
s.e.				0.419
lhuM				0.7677***
s.e.				0.219
ofM				0.0194
s.e.				0.24
cent_cinter				0.1618
s.e.				0.991
cent_compl				0.2002
s.e.				0.119
N	33838	33838	33838	33838

legend: * p<0.05; ** p<0.01; *** p<0.001

2. Defining the Regional Communities of hospital organisations

By using the *Pons and Latapy's walktrap* community detection algorithm, I identified the hospital's communities. I used *igraph* software package in R (Csardi and Nepsz, 2013), I choose this approach because its logic is similar to the process of transferring patients between pairs of hospitals and it is also suitable for weighted network. This approach is one of the several methods that has been developed to identify the community structure (Devi and Poovammal, 2016). This method has been proven to perform better in detecting community structure across different networks (Labatut and Balasque, 2012). One advantage of the community detection method is that it is fully hierarchical in which the structure can be split into subcomponents.

The idea behind this approach is that random walks on a network "tend to get trapped into densely connected parts corresponding to communities "(Pons and Latapy, 2005:1). The algorithm begins with the random walks through the network – a reiteration process in which at each step a random walker is first placed in a hospital of the network. It has the possibility of moving to any linked hospitals related to the number of patients transferred between each dyad of hospitals and the number of other hospitals that the first hospital is linked to (Pons and Latapy, 2005). The algorithm calculates the distance between each hospital based on the probability that the two hospitals are on the same random walk. By using the distance, hospitals are portioned into different communities, capturing their structural similarity: hospitals that are closer together are combined into small communities and then these communities are grouped into larger communities in order to minimize the distance between each hospital and merged communities. To evaluate the distinctiveness of the communities, a final group is created by using the measure called modularity (Pons and Latapy,2005). Modularity measure calculates the proportion of relations among hospitals within – between each community. In the inter-hospital networks, the modularity score is weighted by the strength of each tie. The modularity score ranges from 0 when the communities are no better than random, to 1 when the communities are perfectly distinguishable. However, modularity has some limitations, such as the resolution issue (Fortunato, 2010). The resolution issue means that the size of the observable communities depends on network size. Since the modularity-based method is based on the network size this threshold depends on the size of the whole network, hence the modularity-based will not capture communities of certain size. Therefore, it does not give an intuitive sense of how well the method has been performed. To provide that intuition, I calculated the number of patient transferred within each community and across communities. It means that a better grouping of hospitals would have more ties within each communities (patient transfers within), but also how a better grouping of hospitals interact to each other across communities (patient transfers across).

The results of the community detection method show four different levels: 9 communities in 2006, 8 communities in 2007, 9 communities in 2008 and 8 communities in 2009. As a results, the community structure of the hospitals appears stable (Labaut and Balasque, 2012). Using the methods above, 14 sub-hospital communities were identified in 2006, 19 sub-hospital communities were identified in 2007, 14 sub-hospital communities were identified in 2008, and 10 sub-hospital communities were identified in 2009. In the first two years the percentages of patients transferred across each sub-hospitals communities was 34.9% in 2006 and 29.2% in 2007, while the percentage of patients transferred within each sub-hospital community was 24.1% in 2006 and 21.1 % in 2007. However, the percentages of patients transferred across each sub-hospital communities decreased in 2008 and 2009, because some hospitals were placed into single- hospital communities as described in table 1.

Table 1. *Descriptive characteristics of hospital communities*

Year					
	2006	2007	2008	2009	
	14 H. Communities	19 H. Communities	14 H. Communities	10 H. Communities	
Size	110	110	107	103	
Minimum patients within	0	0	0	0	
Maximum patients within	5920	2960	6771	7141	
Minimum patients across	10	0	0	0	
Maximum patients across	2671	2731	1816	1795	
% of patients within	24.1	21.1	27.5	27.1	
% of patients across	34.9	29.2	15.2	20.4	

To give a better idea of the patient transfer across and within the sub-hospital communities for each year, the figures 2 (a) and (b) show the distribution of patient transfers for each of the sub-hospital communities.

Figure 2(a). Patient transfers across sub-hospitals communities by years

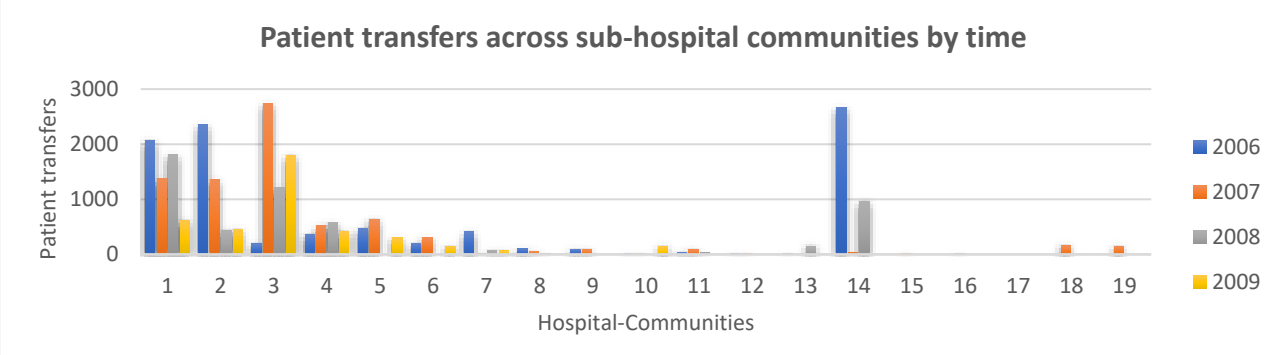
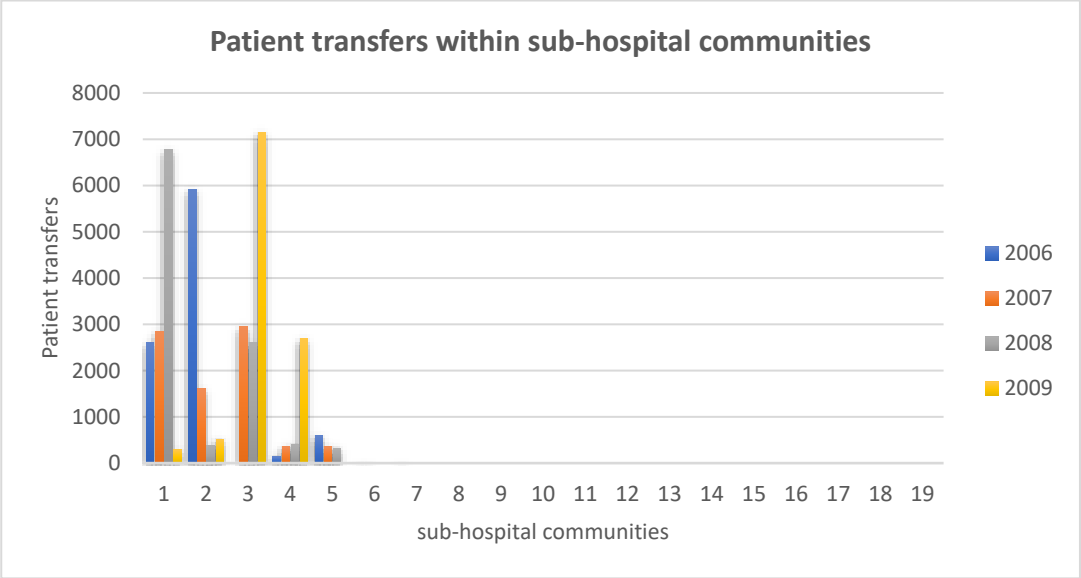
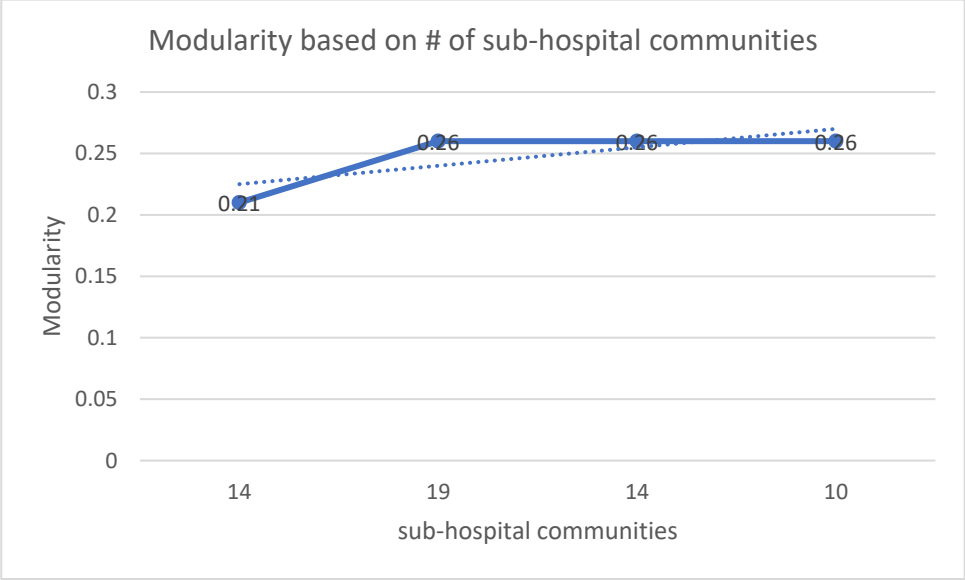


Figure 2(b). Patient transfers within each sub-hospital communities by year



When the communities were identified, the modularity score for each years decreased because the communities were divided into sub-hospital communities as shown the figure 3.

Figure 3. Modularity based on the number of sub-hospital communities by time



The communities were plotted for each of the given years (figure 4), the communities were generally closer together and overlapping in the graph, where the colors of hospitals indicating that they belong to multiple sub-hospital communities. When the communities overlap, it represents that hospitals that

belong to multiple sub-hospital communities are more likely to create ties, hence transfer patients (in my case collaborate) even if they are distant.

Figure 4. Regional communities of hospital organisations by time