ORGANIZATIONAL NETWORK RESILIENCE AFTER UNEXPECTED SHOCKS

ABSTRACT

Organizational resilience can be viewed as the capability of organizations and systems to absorb and adapt to environmental shocks, by either bouncing back to their initial status, or achieving a new, more advantageous equilibrium. Limited research has been conducted on the antecedents to organizational and systemic resilience, and particularly in the context of radical, sudden changes. Particularly understudied is the analysis of relational dynamics in situations of sudden change, when social relationships, their structure and their evolution during environmental shocks or turbulences may be an important antecedent of organizational and systemic resilience. This paper explores how organizations within an open, complex adaptive system modify their social capital to achieve performance resilience, by investigating the modifications of patient referral networks among hospitals in the Abruzzo region as a consequence of the 2009 L'Aquila earthquake. Our findings reveal that the earthquake has an important, although highly-differentiated, effect on the network structure as a whole and on the ego-network structure of regional hospitals. While network structure indicators seem not to be significantly modified by the earthquake and exhibit a substantial stability of the system's performance, social capital structure of the collapsed hospital changes profoundly in the disaster aftermath and these changes are more radical and profound than the those observed in other hospitals in the network. Moreover, our findings highlight that both geographical and social proximity are significant factors underpinning nodes' heterogenous reaction to changes. A discussion of the main theoretical contributions of our findings concludes the paper.

Keywords: Resilience; Social capital; Complex adaptive systems; Healthcare organizations.

INTRODUCTION

Whether and how organizations display resilience in the context of sudden changes or turbulent environments has been attracting increasing attention from organization and management scholars (Sutcliffe & Vogus, 2003; van der Vegt, Essens, Wahlström, & George, 2015). Stemming from the cross-fertilization of several disciplines, spanning across child psychology, engineering, ecology studies, disaster and crisis management (van der Vegt et al., 2015), the concept of organizational resilience is still fluid, in constant evolution, and lacks unified understanding. Nevertheless, a few important studies in the past few years have significantly contributed to advance the understanding of the construct, with a common view that "when uncertainty increases, resilience gains importance in the survival of organizations" (Kantur & Iseri-Say, 2012). And in fact, the concept of resilience generally points to the capability of an organization or system to adapt to disruptive events, thereby ensuring functioning (Allenby & Fink, 2005; Stuart, 2017; Weick & Sutcliffe, 2007; Kahn et al., 2018). In doing so, it may transform its structure and means to adapt to stress, changes, and uncertainty (van der Vegt et al., 2015).

Despite the commendable advancement of prior research in conceptualizing organizational and systemic resilience and exploring its causes and antecedents (Weick, 1993, 1996), it is still not clear how and why some systems – whether organizations or societies – are more resilient than others and under which circumstances (Williams & Shepherd, 2016; van der Vegt et al., 2015). Particularly, relational dynamics in situations of sudden change remain understudied, when in fact social relationships, their structure and their evolution during environmental shocks or turbulences may be an important antecedent of organizational and systemic resilience (Kahn, Barton, & Fellows, 2013; van der Vegt et al., 2015). Observing how

social systems and their composing organizations alter their ties and network structure as a consequence of unexpected, sudden events can result into important insights into how organizations try to re-establish equilibrium and the role of social capital in this process. In fact, resilience of systems' relational ties and social capital after a major change is foundational to support higher order capabilities of systems to repair and transform (Kahn, Barton, & Fellows, 2013).

The relevance of organizational and systemic resilience and its manifestation in the network dynamics of social capital are particularly salient in the case of high reliability organizations (HROs) (Weick, Sutcliffe, & Obstfeld, 1999) – entities for which reliability and safety is more salient than efficiency, because of the large scale, disastrous consequences that organizational failure might entail. Among HROs notable examples are healthcare organizations and hospitals, which are exposed to complex internal environments and highly dynamic external contexts, and are prone to risks and catastrophic failures. Shocks of different nature can deeply affect hospitals activities, such as sudden policy changes that disrupt the regulatory framework, introduction of new technologies, epidemiologic transitions and socio-demographic changes such as population ageing, business model innovations that require new balances between patient outcomes and operational efficiency. Moreover, hospitals' operations significantly rely on relational ties to other hospitals (Kitts et al., 2017; Mascia, Pallotti, & Angeli, 2017). A large body of literature has documented hospitals' embeddedness in their network of patient referrals, and the saliency of this social capital to patient outcomes (Lomi et al., 2014; Mascia, Angeli, & Di Vincenzo, 2015). The question of how hospital referral network react to sudden changes is therefore timely and relevant, to better understand organizational resilience in hospital contexts as well as the larger resilience capability of regional hospital systems.

This paper investigates the effects of sudden shocks on organizations' social capital, with a view to understand whether, to what extent and how inter-organizational networks support the larger system in maintaining functioning and ensuring sustained performance. Resilience often requires profound restructuring of lower levels of the system (van der Vegt et al., 2015), especially because shocks do not always affect systems-as-a-whole but localized parts more than others (Kahn et al., 2018). A paradoxical situation emerges, in which lots has to change – for example at node or relationship level – so that everything can stay the same (Il Gattopardo!). It is therefore plausible to observe important modification of organizations' social capital to avoid systemic perturbance.

In order to conceptualize the theoretical link between organizational and systemic resilience, we apply a complex adaptive systems (CAS) perspective. A view rooted in CAS emphasizes the interrelations between multiple actors within a system and the resulting self-organizing nature of complex systems. These characteristics enable CAS to adapt to external shocks and transition to new states of equilibrium, albeit in often unpredictable ways due to the complexity of the underlying interdependencies (Beck, Ashmos, & Plowman, 2013). Although self-organizing and adaptiveness are considered foundational characteristics of CAS, limited knowledge is available on how such systems evolve and how the complex relations among actors differentially support specific direction of evolution. Empirically, we ground our research during L'Aquila earthquake, a dramatic natural disaster occurred on April 9th, 2009, which caused the destruction and temporary shutdown of one main hospital in the region. Looking at this event as a natural experiment, we study how hospital organizations modify their social capital to deal with the consequences of such radical change. We analyze organizational and systemic social capital in terms of patients' transfer network within the region.

BACKGROUND AND HYPOTHESES

Organizational and systemic resilience

While in psychological studies resilience points to a personality trait that allows individuals to withstand the negative consequence of adverse event and react with optimism (Luthar, Cicchetti, & Becker, 2000; Masten & Monn, 2015), from an ecological perspective resilience indicates system integrity and flexibility, that allow for absorbing shocks in a way that does not majorly compromise system functionality (Holling, 1996). In engineering, resilience measures the extent to which a system can absorb disturbances and return to its natural single state of equilibrium (Holling, 1996; Limnios et al., 2012). In a similar line, in crisis and disaster management research, resilience denotes the capability of an organization or system to "bounce back" to its initial state, after a major crisis or natural calamity (van der Vegt et al., 2015). These viewpoints underline resilience as composed two aspects: a robustness factor, that measures the capability of a system to absorb shock and maintain functionality despite the disturbance, and a rebounding factor, which determines the ability by which systems bounce back to their initial state (Bakker, Raab, & Milward, 2014). With particular application to organizational resilience, Linnenluecke and Griffiths (2010) espouse the first view and argue that resilience can be conceptualized as "the amount of disturbance that an organization can absorb before it looses its structure and function" (Linnenluecke & Griffiths, 2010: 495).

A second line of thought departs from the engineering-led perspectives to also embrace the transformative potential of organizational resilience and the existence of multiple states of system equilibrium. Weick and colleagues (Weick et al., 1999) first argue that, in addition to absorbing change and maintaining functionality, organizational resilience manifests also in the

capability to leverage the change to achieve a new – possibly more advantageous – state of equilibrium (Kahn et al., 2013). Organizational resilience is increasingly seen as a dynamic capability that "implies pre-event readiness for a disruptive event, post-event response for appropriate and timely recovery, and creative renewal capacity through improvisation" (Kantur & Iseri-Say, 2012: 764). In one of the most recent contribution on the topic, Ortiz-de-Mandojana & Bansal (2015: 1615) systematize organizational resilience as the "ability of organizations to anticipate, avoid, and adjust to shocks in their environment".

The study by Mamouni Limnions and colleagues (Limnios at al., 2014) provides a third, important step in advancing the conceptualization of organizational resilience. The authors recognize that system resilience is not necessarily beneficial nor should be sought for per se. Rather, the benefits of resilience should be considered in relation to the desirability of the initial status. Polluted environments, societies disrupted by conflicts and unable to regain social cohesion, corrupted socio-political systems that are unable to re-enforce legality, marginalized and underprivileged communities that cannot afford education or good quality healthcare services and are hence bound to see their income chances further deteriorating, are all examples of how rigidity or poverty traps create inertia and fix systems in undesirable statuses. It is especially in these contexts that the meaning of organizational resilience departs from a "bouncing back" function to instead evoke the potential for transformation. Organizational resilience here denotes the capability to achieve a new, more favorable status of equilibrium, thus leveraging the shock wave produced by the disturbance in a transformative way.

Against this definitional backdrop, organizational resilience can be viewed as the capability of organizations and systems to absorb and adapt to environmental shocks, by either bouncing back to their initial status, or achieving a new, more advantageous equilibrium. Limited

research has however been conducted on the antecedents to organizational and systemic resilience, and particularly in the context radical, sudden changes (Linnenluecke, Griffiths, & Winn, 2012). As a consequence, it remains still largely unclear why and how some systems and organizations manage to be more resilient than others. A notable exception, in the context of a sudden disruptive event such as the Mann Gulch fire where 13 people died, the work by Weick (1993) indicated improvisation, virtual role systems, the attitude of wisdom, and norms of respectful interaction as sources of resilience within groups, which prevented the organization from disintegrating. In a situation of gradual change distributed over time, Pal and colleagues (Pal, Torstensson, & Mattila, 2014) investigated organizational resilience of Swedish SMEs active in the textile industry during two waves of economic crises. Their study highlights how resourcefulness (in terms of quantity and variety of material, financial, intangible, social and network assets and resources), dynamic competitiveness (with attributes such as flexibility and redundancy and robustness) and learning and culture (such as attention to employee well-being and collective sense-making) determine higher level of organizational resilience.

In a conceptual study, Kantur and Iseri-Say (2012) identify perceptual stance, contextual integrity, strategic capacity and strategic acting as determinants of organizational resilience. Because these contributions focus on intra-organizational mechanisms, only the study by Pal and colleagues (2014) marginally touches upon network and social connections as an asset for achieving resilience, and none of these works investigates the link between organizational and systemic resilience. The value of social capital as an antecedent to resilience for both organizations and the larger systems they are embedded into is therefore largely understudied. By investigating the modifications of patient referral networks among hospitals in the Abruzzo region as a consequence of the 2009 L'Aquila earthquake – which caused the collapse of one of

the most crucial hospital facilities – provides an unparalleled opportunity to analyze whether and how hospitals' network enabled organizational and systemic resilience.

Complex adaptive systems

In order to understand how organizations and larger systems can achieve resilience, we advance here a theoretical perspective informed by complex adaptive systems (CAS) theory. The theoretical underpinnings of CAS reside in general system theory (Bertalanffy, 1951; Boulding, 1956), which introduces the concept of open systems as aggregations of parts connected by inter-dependent relationships, which also evolve in interaction with their environment towards a natural status of equilibrium or homeostasis (Boulding, 1956; Katz & Kahn, 1978; Schneider & Somers, 2006). Complex adaptive systems are specific types of open systems featuring a number of defining characteristics. First, their *complexity* is due to the high number of parts and of interactions composing the system. Each part behaves according to rules that relate it interactively to other parts. Interaction are usually – but not necessarily – local and very numerous (Maguire et al., 2006). The *adaptiveness* of CAS implies that the rules governing the actors' behavior within the system evolve over time, along with learning processes and accumulation of experience of the actors themselves. As such, CAS are *nested* in other CASs, and each systemic actor can be viewed as a CAS itself. By responding to changes in its local context, each actor – without having an overarching systemic view and without coordination with other parts – modifies its behavior and causes emerging changes at systemic level, which identifies the *self-organizing* nature of systems (Maguire et al., 2006). Because such changes are not predictable by looking at the properties of the parts, but are caused by the complex chains of interactions among parts, CAS are typically view as *unpredictable.* As such, they can be fully

understood and appreciated only through a holistic view, which emphasizes the whole as a different entity than the sum of its part, in contrast with the typical reductionistic approach of early 20th century science.

Open systems such as CAS display the highest level of complexity among natural systems (Boulding, 1956) and evolve by the principle of self-maintenance, which they achieve by exchanging energy with the external environment through permeable system boundaries. In particular, it is the absorption of energy from the external environment that allows for the emergence of orderly patterns within the systems (Katz & Kahn, 1978) – which qualifies CAS as *dissipative structures* (Baker, 1993; Prigogine, 1996). And in fact, organizations under strain of disaster operate "far from equilibrium" (Madsen, 2009; Rudoplh & Repenning, 2002). Because the interactions among actors are rich and heterogeneous, *non-linear* reactions can emerge, where disproportionately large effects may ensure from small changes, and vice-versa (Kauffmann). Also, effects of change can manifest with significant time lags, and at large geographical distances, even though actors' interactions tend to be local and contextual. Accordingly, properties of the system may be the effect of the behavior of its parts, rather than as a reaction to the environment (Holland, 1998; Morel & Ramanujam, 1999; Schneider & Somers, 2006). Non-linearity highlights the importance of initial conditions to understand future states of CAS, and hence the inherent path-dependency of such systems (Kaufmann, 1993; Sterman, 2000).

Complex adaptive systems and systemic resilience

We apply the lens of CAS to investigate whether and how organizations within an open, complex adaptive system modify their social capital to achieve performance resilience, in a situation of

radical change. In our case, the sudden shock is represented by the 2009 Aquila earthquake, which caused the temporary shutdown of one of the hospitals within the regional healthcare system. This theoretical grounding allows for a number of considerations.

First, performance resilience – intended here as the capability of a system to maintain its level functioning – can be viewed as the status of equilibrium or homeostasis that open systems and CAS in particular tend to maintain. Under the powerful trigger of a radical change such an earthquake and the collapse of a central hospital in region, adaptive behavior of hospitals will be generated as well as new configurations of their complex interactions, in a process of self-organization, to maintain systemic equilibrium. At the same time, while social capital may be an important antecedent to ensure systemic resilience, the referral network might transition in the process to new states of equilibrium corresponding to new levels of systemic functioning, and not bounce back to the previous stage. In this sense, co-evolutionary patterns between social capital configurations and system resilience might be observed, in which they are both the effect and the cause of each other. We therefore argue that changes in the structure of relations across nodes – hence changes of the whole network structure of patient referrals among hospitals – will be strongly associated with changes in the system performance. More formally:

Hypothesis 1 (HP1): The larger the changes in the whole hospital referral network structure in the disaster aftermath, the higher the variation in the healthcare system performance.

Moving from considerations about the whole network structure to focus on the changes undergone by individual system parts, the CAS perspective allows to develop hypotheses on the relational behavior of the individual nodes. Because of the nested nature of CAS, each

organization within a system can be considered as a CAS itself. Therefore, under a situation of strain, stress and uncertainty affecting the whole system and/or some of its parts, changes are likely to emerge in the social capital of the individual organizations, to enable them to ensure resilience of their own operations, in line with the self-organizing, emergent nature of CAS (Beck, Ashmos Plowman, 2014). Also, because CAS behavior cannot be inferred by the characteristic and behaviors of the composing parts, and vice-versa, lower level alterations – hence social capital changes at the level of individual organizations – can be of entirely different nature than the alterations observed at higher, system level. And in fact, systems may maintain functioning, and hence ensure resilience, by undergoing profound internal changes of structure and means (van der Vegt et al., 2015). Therefore, while the system as a whole may display the capability to bounce back to the original state or just maintain its level of performance and functionality throughout, this might not be the case for individual organizations and their social capital, which might instead permanently transition to new states.

Complex systems affected by sudden turbulence are rarely under strain in a homogenous way. Rather, some systemic parts are more affected than others, and the stressful even trickles down from one system are to another (Khan et al, 2018). Individual nodes are therefore likely to develop heterogenous response, that relate in unpredictable, non-linear ways to the magnitude of the strain they are exposed to through their complex systems of interactions with the affected part. In our specific case, the 2009 L'Aquila earthquake determined the collapse of one large hospital in the main city of the region Abruzzo, which in our conceptualization constitutes the area posed under highest strain. Following the above reasoning, we argue that the structure of this hospital's social capital – manifested in its ego-network – is likely to undergo radical changes in the period immediately following the disaster, and that these changes will be

significantly different than the ones observed in other hospitals in the network. We formalize our second hypothesis as follows:

Hypothesis 2a (HP2a): The ego-network structure of the collapsed hospital in the disaster aftermath will be significantly different from its original state.

Hypothesis 2b (HP2b): The ego-network structure of the collapsed hospital in the disaster aftermath will display significantly higher alterations than the other hospitals in the network.

Although not as dramatic as the changes observed for the collapsed hospital, modifications of hospitals' social capital are likely to emerge also for the hospitals in the system. To ensure system resilience, changes in the collapsed hospital's ego-network structure will be compensated by other organizations, which will manifest in changes in their referral network. While the number, the nature and far-fetched extent of the interactions among the organizations is inherently unpredictable, a CAS perspective advances that higher changes will be observable locally and simultaneously to the most affected section of the system. We argue that hospitals' proximity – both social and geographical – to the collapsed facility can help explain heterogeneity in hospitals' ego-network changes. Geographical proximity strongly influences the propensity of organizations to collaborate and exchange knowledge and resources (Sorenson & Stuart, 2008; Ter Wal, 2014; Mascia, Angeli & Pallotti, 2017). In the case of hospitals, this is particularly true because closely located facilities are more likely to compete for the same patients, as well as to refer patients to each other, in order to minimize patients' travelling and time (Mascia et al, 2017). It follows that, if a hospital's operations are suddenly severely impaired, such shock will spill over and mostly impact the nearby hospitals, which will manifest

in higher changes in their ego-network in the aftermath of the disaster. Likewise, we argue that social proximity – a form of proximity that considers the existence of prior relational ties between two nodes (Ter Wal, 2014) – will play a role in determining the magnitude of hospitals' experienced shock and the relative ego-network changes. It is well-documented that hospitals choose patient transfers' destination hospital according to specific protocols and pre-existing coordination routines, which have built over time through repeated collaboration (Veinot et al., 2012). If a hospital is removed from the network, depending on the structure of the network and positional characteristics of the specific node (Kahn, Barton and Fellow, 2013), consequences for the hospitals' more proximate collaborators are likely to be more severe, and hence to manifest in higher social capitals' alterations. We advance the following two hypotheses:

Hypothesis 3 (HP3): The higher the hospital's geographical proximity to the collapsed hospital, the larger the larger the structural changes of its ego-network.

Hypothesis 4 (HP4): The higher the hospital's social proximity to the collapsed hospital, the larger the structural changes of its ego-network.

METHODS

Research setting

An earthquake measuring 6.3 on the Richter scale hit the region of Abruzzo (Italy) at 3:30 a.m. on April 6th, 2009. More than 300 people died, around 2000 injured and 70'000 were left homeless. Several strong aftershocks hit the region in the following week. The epicenter of these devastating series of earthquakes was located close to the city of L'Aquila, the regional capital. The city hospital, San Salvatore, was heavily damaged. A wing of the building collapsed during the earthquake, many others have reported structural damages making them unusable.

Notwithstanding the fact that the building was severely damaged, the operators, doctors and nurses continued to respond to the overwhelming quantity of calls, and coordinated rescue missions with the support of the local emergency hotline ("118"). Around 2 PM of April 7th, the hospital was closed due to the heavy damage it sustained, and was entirely evacuated for safety reasons. In a matter of hours, in the large square in front of the San Salvatore, the Red Cross mounted a temporary "field hospital" to deal with emergencies. In the meantime, the calls and coordination of rescue operations were routed through an emergency coordination center created within the gymnasium of the Financial Guards barracks, in another part of the city.

This study setting seems to be particularly appropriate for the purpose of this research. Abruzzo is a region in central Italy with a population of approximately 1,300,000 residents. In the Abruzzo regional health system, health care services are provided by 35 hospitals (22 public and 13 private). Of the 22 public hospitals, two are teaching hospitals. Public hospitals provide highly specialized hospital care. Teaching hospitals are linked to universities, and provide education, research, and tertiary care. Private hospitals are investor-owned organizations partially financed by the regional healthcare service, providing ambulatory assistance, hospital care, and diagnostic services.

The tragic occurrence of the earthquake makes Abruzzo a unique case study, which can help to shed light on how a collaborative network of hospital organizations is affected by such unexpected event. In particular, the earthquake has severely damaged hospital San Salvatore (ID 130001 in our analyses) – one of the most important nodes of the overall hospital network. This hospital is indeed located in L'Aquila, the capital city of the region, and is a major teaching hospital, representing the second largest hospital in the region in terms of number of staffed beds.

Data and Measures

In the present paper, we use data provided by the Abruzzo Agency of Public Health – a regional agency that routinely collects administrative discharge data for the purpose of assessing regional hospitals' activities and performance. Administrative data were used in the present study to identify patient transfers between regional hospitals, defined as elective patients transferred from a given hospital (sender) to another hospital (receiver) (Lee et al., 2011). Patient transfers typically require a considerable level of coordination and communication between partners, and are thus considered as a reliable indicator of the presence of an underlying collaborative relation between hospitals (Lomi et al., 2014; Mascia, Angeli & Di Vincenzo, 2015). Patient referral relations also represent a clear example how hospitals may collaborate to improve the quality of care that they can deliver to patients, and ensure better clinical outcomes (Lomi et al., 2014). Administrative data on hospital activities (discharged patients, average length of stay), size (staffed beds), and institutional profile (private vs. public) were also accessed and used in our analyses.

Given our interest towards the study of network and social connections as antecedents of resilience processes, we adopt a social network perspective to explore inter-organizational patient transfer patterns in the region. We builded several 35 x 35 adjacency matrices, in which rows and columns report the regional hospitals and intersection cells contain the patient transfers between hospital pairs. We examine the dynamic of patient transfer networks for a sufficient time before and at the same time after the disastrous event by building forty-eight different networks – one for each month covering 12 months before and 36 months after the earthquake (12*36= 1260 observations), as we aim to capture the impact of the earthquake on the inter-hospital network.

To test our theoretical predictions, we rely on several indicators that capture network

properties of the overall network as well as single hospitals' ego-networks. At the network level, we consider density, centralization and closure (Wasserman & Faust, 1994). Network *Density* is generally defined as the number of actual ties in a network out of the total possible ties that can be observed in the network. *Centralization* indicates the extent to which network ties are concentrated around one or few nodes; in highly centralized networks network ties revolve around only one node whereas in decentralized networks ties are more distributed involving other network nodes. *Closure* captures the level of clustering of the whole network considering the extent to which two connected network nodes show many mutual ties to third actors.

The ego-network measures we consider are: Ego-network size, Brokerage, Density, Constraint. *Ego-network size* provides the number of alters directly connected to the ego (focal hospital), and hence offers a measure of the hospital's relational activity in a specific time period. *Brokerage* calculates the number of times an ego lies on the shortest path between two alters (i.e., the number of pairs of alters that are not directly connected) (Borgatti, Everett, & Freeman, 2002), hence providing a measure of how ego connects otherwise disconnected alters (Heinze & Bauer, 2007). *Density* calculates the number of egos' ties divided by the number of pairs and thus expresses which percentage of all possible ties in each ego network is actually present (Borgatti, Everett, & Freeman, 2002). Finally, *Constraint* provides an indication on the extent to which ego is connected to partners who are connected in others of ego's alters (Burt, 1992). All network measures are computed by using the software package Ucinet VI (vers. 6.598) (Borgatti, Everett, & Freeman, 2002).

We also consider two variables that capture the hospital activity, namely *Number of discharged patients* and *Average length of stay*, calculated by dividing the number of bed-days by the number of discharged patients during the year, as well as two indicators reflecting the

geographical and social proximity. *Geographical proximity* expresses the distance between each hospital (expressed in kilometers) and the epicenter of the earthquake. *Social proximity* is a dichotomous variable taking 1 if hospitals exhibit a direct tie before the disastrous event, and 0 otherwise.

Model Specification

To model the consequences of the earthquake on hospitals' networks we rely on interrupted time series (ITS) analyses, which can be considered as the strongest quasi-experimental design for testing longitudinal effects of time-bounded shocks such as organizational or policy interventions (Cook & Campbell, 1979; Lagarde, 2011; Valentine & Edmondson, 2014), health technology assessment (Ramsay, Matowe, Grilli, Grimshaw, & Thomas, 2003) or natural disasters (Milojevic et al., 2011). In their most sophisticated and most internally valid form, ITS designs compare the trend of an outcome variable before and after a shock occurs and between an intervention group (individual or entities exposed to the shock) and a control group (Linden, 2015; Linden & Adams, 2011). Data are therefore collected at multiple instances over time for both control and intervention group before and after the intervention point. ITS analyses are then able to detect whether the trend after the intervention is significantly different than the historical trend, and between groups.

In our ITS design, the intervention group was formed by the hospital that has collapsed during the earthquake (Hospital 130001), while all the other hospitals have been considered part of the control group. In such a configuration, seven covariates enter the model, as illustrated in Fig 1.

Figure 1 about here

T is the time elapsed since the start of the observation period, X denotes the time of the intervention (1 for postintervention period, 0 otherwise) (and Z is a dummy variable that distinguishes the intervention group from the control group (1 for the intervention group, 0 otherwise). By introducing in the model the interactions of these four terms (XT, ZXT, ZX and ZT), ITS design computes seven coefficients, with the following meaning. β_0 denotes the intercept of the control group before the intervention, β_1 (T) measures the slope of the outcome variable before the intervention for the control group, β_2 (X) measures the difference in level (intercept) of the trend after the intervention and β_3 (XT) represents the slope of the outcome variable curve after the intervention for the control group. For the intervention group, β_4 (Z) represents the difference in intercept between the intervention and the control group before the intervention, β_5 (ZT) represents the difference in slope between intervention and control group preintervention, β_6 (ZX) measures the difference in the levels of the outcome variables between intervention and control group immediately after the intervention and β_7 (ZXT) represents the difference in slop between the intervention and the control group after the intervention has taken place.

In our analyses, ITS regressions are performed by using Newey-West standard errors to correct for autocorrelation across consecutive observations for the same unit. We use software STATA 15 for ITS analyses.

ANALYSIS AND RESULTS

In our study, we investigate the effect of the earthquake on the inter-organizational patients' referral network in the Abruzzo region, particularly looking at the impact of the event on the overall network structure and single hospitals' ego-network structure.

The first hypothesis we formulated (HP1) argues that, after the occurrence of an exogenous shock, the changes in the whole hospital network structure are positively associated to the variation in the system performance. We test HP1 by Mann-Kendall trend tests and graphical analysis. The overall network metrics included are degree centralization, density, and closure.

Figure 2 about here

Their trends are depicted in Figure 2. Figures 3a and 3b display the time series of total hospital discharges and average length of stay.

Figure 3a and 3b about here

Our trend analysis of the overall inter-hospital network structure before and after the earthquake reveals that the overall patient transfer network was not dramatically affected by the disastrous event. In fact, we observe a general tendency of the system to maintain its level of

activities together with a substantial stability of the relational structure of the whole network. We found no significant differences in the trend period for degree centralization (Kendall's τ = 0.067; p = 0.576), density (τ = -0.005; p = 0.978), and closure (τ = 0.114; p = 0.333). Similarly, Mann-Kendall trend tests reveal no differences in performance measure across periods, neither for total hospital discharges (τ = -0.262; p = 0.064) nor for the average length of stay (τ = 0.133; p = 0.362). Hence, our findings seem to demonstrate that resilience plays a role: network indicators seem not to be significantly modified by the earthquake and this corresponds with substantial stability of the system's performance. Altogether, these results support H1.

In the second group of hypotheses (HP2a and HP2b), we argue that the ego-network structure of the collapsed hospital (San Salvatore, the closest to the epicenter and thus our intervention unit) is significantly different for its original status as a consequence of the exogenous shock (HP2a). Moreover, we argue that the ego-network structure of the collapsed hospital will display significantly higher alterations than the other hospitals (control group) in the network after the shock (HP2b). To test our hypotheses, we take into consideration the following ego's social capital dimensions: *Ego-network size, Brokerage, Density, Constraint*.

ITS regressions document that the earthquake significantly changes the structure of social capital of the hospital close to the epicenter. We run four different models to understand the effect of the earthquake on the inter-hospital network of patient transfers over time. Each model explores the impact of the disastrous event on ego-network size, brokerage, density and constraint. As specified in the statistical analysis section, our models afford comparing the trend of four ego-network variables before and after the earthquake and between the focal hospital (intervention group) and all other non-affected hospitals (control group). The ITS regressions

results are reported in Table 1, while Table 2 displays the comparison of Linear Postintervention Trends.

Tables 1 and 2 about here

Figures 4a-4d plots the time series of ego-network characteristics in the overall time window (36 months) for the focal hospital and the average control group, before and after the earthquake.

Figures 4a-4d about here

The comparison of focal hospital's linear trend before and after the earthquake and graphical analysis reveal that three out of four social capital measures are significantly affected by the exogenous shock. In other words, it seems that the ego-network's original state of hospital 130001 exhibits substantial changes after the earthquake, particularly in the case of ego-network size (coeff= 0.0908; p=0.0404), brokerage (0.0245, 0.0025) and density (1.0090; 0.0370) (see Table 2).

Altogether, these findings allow us to support our HP2a, since they confirm a statistically significant variation in the structure of focal hospital's social capital.

In order to test HP2b, we consider the comparison trend test post intervention results,

which display differences between control (hospital 130001) and intervention group (all the other hospitals in the network). Our findings reported in Table 2 show that three out of four social capital measures are significantly different across groups. Particularly, ego-network size (coeff= 0.0984; p=0.0367), brokerage (0.0264; 0.0016) and density (1.0918; 0.0309) exhibit a significant difference between groups after the intervention.

Such result is also confirmed by ITS regression model. In Model 1, where the dependent variable is *Ego-network size*, significant parameters that support HP2b are "*Z*", "*ZT"*, *"ZX12"* and "*ZXT(12)".* The parameter "*ZX12*" displays that there is a negative and significant effect of the earthquake on the ego-network broker of the focal hospital compared to that of other providers, so that the change in the curve intercept after the shock is significantly higher for the focal hospital than for the control group (β_6 = -3.1442; p < 0.01). Also, the parameter "*ZXT(12)*" suggests a statistical difference in the post-shock slop of the focal hospital with that of other hospitals in the region (β_7 = 0.2805; p < 0.01). Findings of Model 2 document that also for the *Brokerage* variable the initial level difference between hospital 130001 and all other regional hospitals is positive and significant (β_4 = 0.3868; p < 0.001) and that there is a negative and significant effect of the earthquake on the post-shock level of ego-network brokerage of the focal hospital compared to that of other providers (β_6 = -0.7208; p < 0.001). We also consider Model 3 in which the outcome variable is *Density*. As reported in Table 1, density tends to decrease marginally and significantly ($\beta_{1=}$ -0.7135; p < 0.1).

Finally, our results document that the following parameters are significant for Model 4 where the dependent variable is *Constraint,* namely "*Z*" and "*ZX*(12)". The parameter for the variable "*ZX(12)"* is marginally significant (β_6 = 0.6919; p < 0.1) suggesting that the earthquake significantly increases the initial level of the focal hospital's ego-network constraint. Altogether,

these findings support our HP2b.

In the third hypothesis we argue that a higher hospital's geographical proximity to the collapsed hospital is positively associated to its larger ego-network structural changes. ITS models show that the all the social capital measures are strongly affected by the distance from epicenter. Particularly, geographical proximity positively influences ego-network *Size* (0.0195; p <0.05), *Brokerage* (0.0025; p <0.05) and *Density* (0.1084; p <0.05), while it negatively and significantly impacts the *Constraint* measure (-0.0019; 0.0003). These findings support our H3.

Finally, according to our hypothesis H4, social proximity to the collapsed hospital is positively associated with a structural change of its ego-network. According to our models, three out four social capital measures are affected by the social proximity, namely *Ego-network size*, *Brokerage* and *Constraint*. Social proximity influences positively *Ego-network size* (3.5834; p <0.05) and *Brokerage* (0.4052; p <0.05) and negatively the *Constraint* (-0.5745; p <0.05).

DISCUSSION

This study has analyzed how a network of hospital organizations reacts to an unexpected event, a shock caused by an earthquake, and redefines over time its collaborative relationships. To model the consequences of this natural disaster on hospitals' networks we used and combined the theoretical lenses of organizational resilience and complex adaptive systems with the tools and methods of social network analysis and interrupted time series (ITS) analysis.

Our findings reveal that the earthquake seems to have an important, although highly-differentiated, effect on the social capital structure of the network as a whole, as well as on the social capital ego-network structure of the sampled hospitals. Indeed, our results overall suggest that the network as a whole shows resilience, i.e. the capacity to adapt and absorb strain and

preserve functioning despite the presence of adversity (Allenby & Fink, 2005; Sutcliffe, 2011; van der Vegt et al., 2015). More specifically, the results of the empirical analyses indicate that, in the observed time period, there are no significant variations in the trend of network characteristics and performance measures, namely total discharges and average length of stay. Although the disastrous event has damaged a very important node of the network, the system as a whole displayed the capability to bounce back to the original state, maintaining its level of performance and functionality.

However, the analysis of single hospitals' ego-network structure before and after the disaster document that the social capital structure of the collapsed hospital profoundly changes in the disaster aftermath, especially if compared with other hospitals. To explain how hospitals redistribute or form new relations we used the theoretical construct of proximity, operationalized here in its geographical (distance from the earthquake epicenter) and social (prior relational ties between two hospitals) characteristics, as they have been largely employed in the studies on the antecedents of network formation (Mascia, Pallotti, & Angeli, 2017). Our results show the existence of a real "shock wave" of the earthquake on hospitals' relational structures for both proximity dimensions.

Overall, these results deliver three important contributions. First, they demonstrate for the first time that some network characteristics are more resilient than others in the context of exogenous, disastrous events. Second, they highlight the heterogeneity in how the sudden shock is absorbed by the network system, in showing how geographical and relational attributes determine differences in the ego-network changes that hospitals experience and enact. Third, our evidence suggests new avenues of research in the relationship between ego-network and whole networks, and shows complex patterns of co-evolution and dependencies. Future studies are

encouraged to illuminate "why" some network properties of organizational social capital are more or less resilient, and how organizational and systemic attributes play a role.

This study provides insights to two main lines of contribution. One considers the role of social capital and inter-organizational ties in supporting organizational and systemic resilience. This study is the first to consider how organizational resilience can manifest through organizations' social capital, and at the same time to test how social capital supports organizational resilience. Being resilience a latent, path-dependent construct (Ortiz-de-Mandojana & Bansal, 2015), it is inherently difficult to observe and measure. In the hospital context, inter-organizational collaborative ties are a foundational aspect of organizational operations, in that they ensure care continuity as well as efficiency and effectiveness. Whether and when hospitals are able to re-establish their social capital structure after a sudden shock is therefore an important indicator of the hospitals' capability to reconstitute the same set of resources able to ensure the same, pre-shock level of activity. The collapsed hospital in our sample inverts its ego-network size trend before and after the shock: while a mild decrease in ego-network size before the earthquake could be appreciated, probably to concentrate the social capital on fewer, more stable partners, after the earthquake the need to rapidly regain operational levels translates into a sharp increase of relational activity over time. This finding points to the fact that social capital is used as a tool to achieve resilience, thereby constituting an indirect proxy of resilience itself.

On this line, our study provides evidence that resilience of the *structural role* of the hospital within its ego-network seems to be more difficult to achieve. Although the number of direct partners reaches pre-shock level at the end of the observation period, the network after 48 months appears significantly more constrained. The level of brokerage reaches levels comparable

to the baseline, however the rate at which brokerage increases is not different than pre-shock values. This evidence suggests that while reconnecting to the same direct partners is relatively easy, reconstituting indirect ties is less straightforward, and the levels and rate cannot be altered or controlled with a deliberate strategy. Routines seem to be in place to rapidly structurally rearrange the network when a node goes missing, so at to ensure the network functionality, however the reabsorption of the specific node in its structural role cannot be taken for granted.

The second line of contribution speaks to the complex adaptive system literature and its application to organization and management phenomena (Beck & Plowman, 2014; Schneider & Somers, 2006). While self-organization, especially under shock, is a well-known property of CAS, the processes leading to systemic re-organization and the heterogeneous roles of different nodes in absorbing the shock and guiding systemic change are unknown. Instead, a widespread perspective assumes that shocks homogenously affect systems and networks in all their parts, thereby ignoring the "geography of strain" (Kahn et al., 2018). Our evidence shows that while the system as a whole is resilient in way it maintains its performance and level of functioning, this is sustained by changes at the level of individual nodes, and particularly in their relational network. This is in line with CAS theory, which predicts that exogeneous shock will triggers orderly patterns of change, which will help the system maintain equilibrium. Also, changes at the node level could be entirely different that changes observed at systemic level, which is what the hospital network in Abruzzo shows in the aftermath of the earthquake. However, the perturbance experience by the nodes is not homogenous, and some hospitals are more affected than others. Our analyses are able to establish that geographical and social proximity as significant factors underpinning nodes' heterogenous reaction to changes. This finding on the side further specifies the nature and direction of geography of strain, on the other side opens up new research direction

in the CAS literature on how different system regions differentially absorb shock and evolve over time.

The present study is not free of limitations. First, the timeframe adopted in this study is limited, and this affects the processes of network change observed after the occurrence of the disastrous event. The adoption of a broaden timespan would likely reveal different patterns of resilience for other relevant network properties, such as constraint and brokerage. A second important limitation concerns the particular setting in which we study network resilience. Healthcare is indeed a high regulated setting in the Italian NHS in light of the various stakeholders (government, regional bodies, local authorities etc.) that are involved in the delivery of public services to the population. As such, the idiosyncrasies of hospital organizations in this health system limit the generalizability of our findings to other organizational fields. Future studies should clarify the extent to which our observed patterns of network resilience characterize organizations also in other industries, as well as the role of external stakeholders in triggering resilience. We believe these represent important research avenues for scholars engaged in the study of organizational resilience.

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Table 1: ITS regression results predicting hospitals' ego-network structural properties.

Variables	Network Size	Brokerage	Density	Constraint
T	-0.0452	-0.0084	-0.7135†	0.0017
	(0.0503)	(0.0070)	(0.4233)	(0.0070)
Z	3.0693***	0.3868***	12.9582†	-0.3714 †
	(0.5478)	(0.0880)	(7.5270)	(0.2176)
ZT	-0.1821*	0.0171	-0.1631	0.0028
	(0.0835)	(0.0139)	(1.2734)	(0.0490)
X12	0.5459	0.0896 †	7.8332*	-0.0207
	(0.3935)	(0.0530)	(3.3749)	(0.0566)
XT(12)	0.0376	0.0065	0.6307	-0.0011
	(0.0533)	(0.0073)	(0.4488)	(0.0075)
ZX(12)	-3.1442**	-0.7208***	-10.2517	0.6919†
	(1.0699)	(0.1696)	(9.5212)	(0.4006)
ZXT(12)	0.2805**	0.0093	1.2549	-0.0102
	(0.0864)	(0.0158)	(1.3836)	(0.0485)
Geographical distance (distance from epicenter)	0.0195***	0.0025***	0.1084***	-0.0019***
	(0.0019)	(0.0003)	(0.0183)	(0.0003)
Social Proximity	3.5834***	0.4052***	-2.2264	-0.5745***
	(0.3014)	(0.0294)	(1.4136)	(0.0428)
Intercept	-0.2436	0.0198	8.0886*	0.1181*
	(0.3403)	(0.0505)	(3.2755)	(0.0489)
Prob > F	0.0000	0.0000	0.0000	0.0000
N of obs.	1260	1260	1260	1260

*Note: Newey-West standard errors in parentheses; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$.*

Table 2: Comparison of Linear Postintervention Trends.

Linear Trend	Network Size	Brokerage	Density	Constraint
Treated	0.0908** (0.0442)	-0.0245** (0.0081)	1.0090** (0.4833)	-0.0067 (0.0057)
Controls	-0.0076 (0.0160)	-0.0019 (0.0020)	-0.0828 (0.1474)	0.0006 (0.0022)
Difference	0.0984** (0.0470)	0.0264** (0.0016)	1.0918** (2.1609)	-0.0073 (0.0062)

*Note: Newey-West standard errors in parentheses; *** $p < 0.001$; **$p < 0.01$; * $p < 0.05$; † $p < 0.1$.*

Figure 1: Graphical representation of an interrupted time-series design (ITS) comparing a control group (lower line) and an intervention group, before and after the intervention (Source: Linden and Adams, 2011).

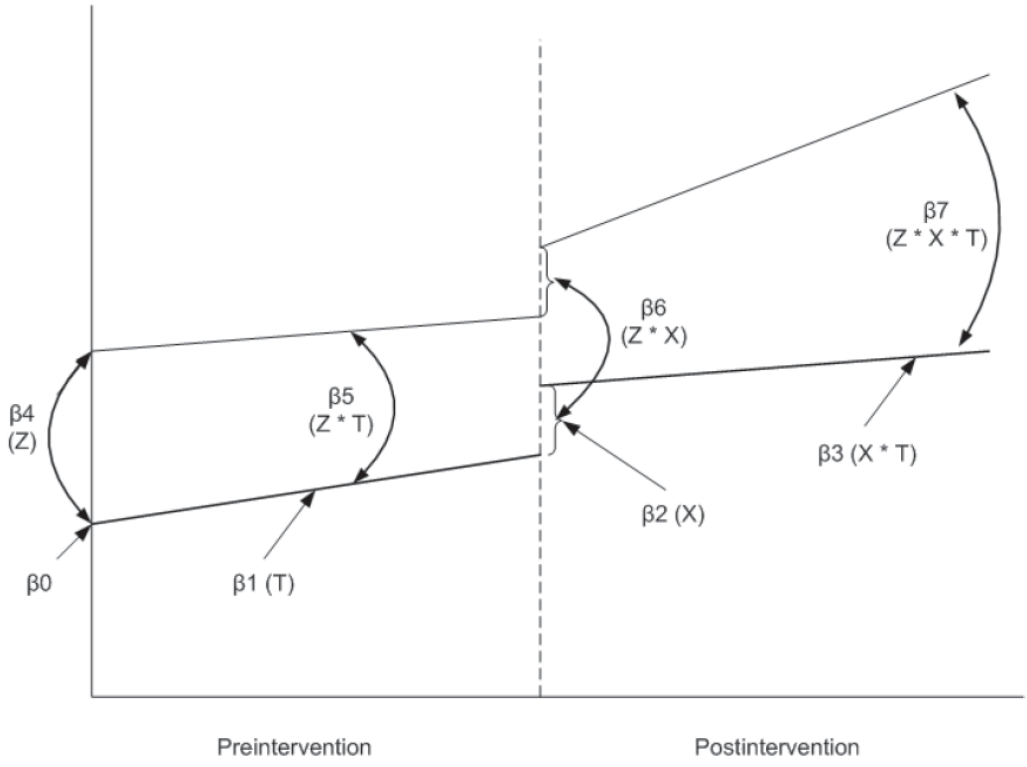
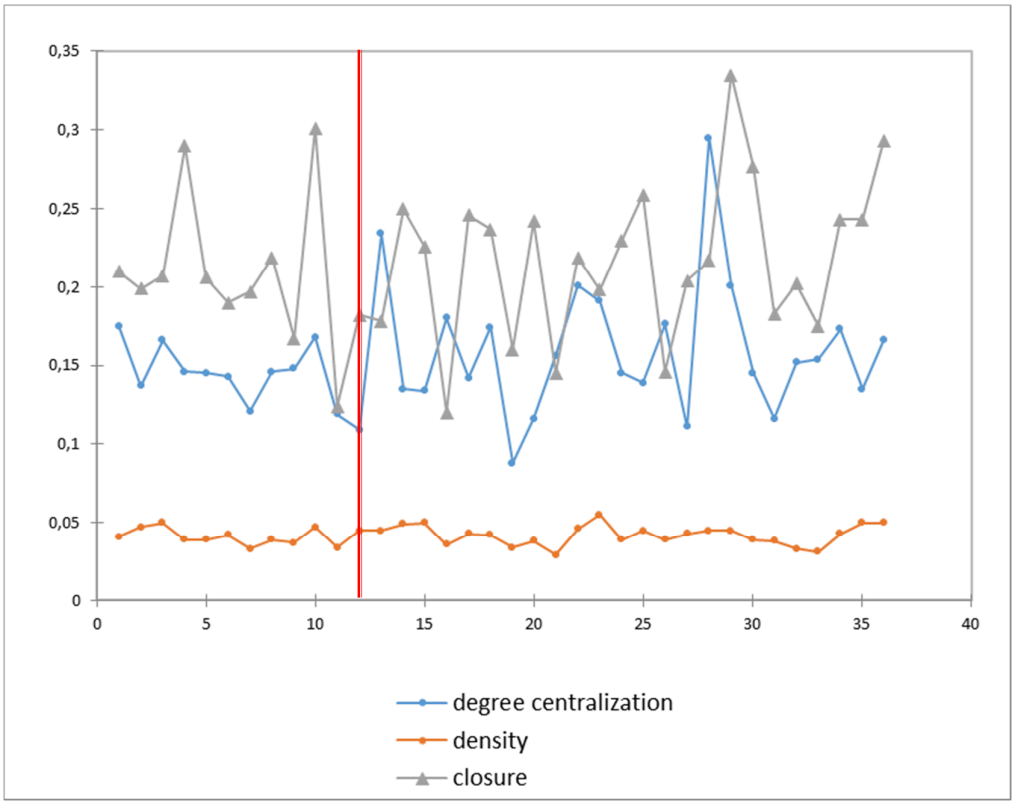
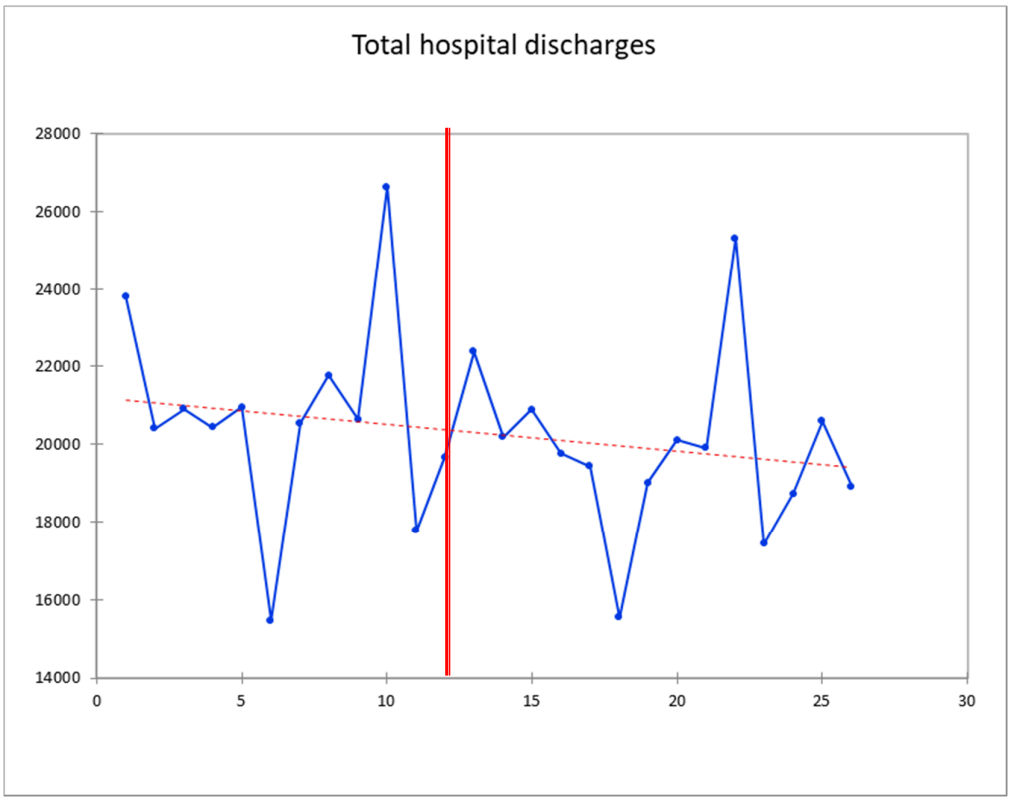


Figure 2: Trend of the overall network structure's centralization measures (degree centralization, density and closure).



Figures 3a-3b: The time series of total hospital discharges and average length of stay and the sequential version of the Mann–Kendall test for the period.



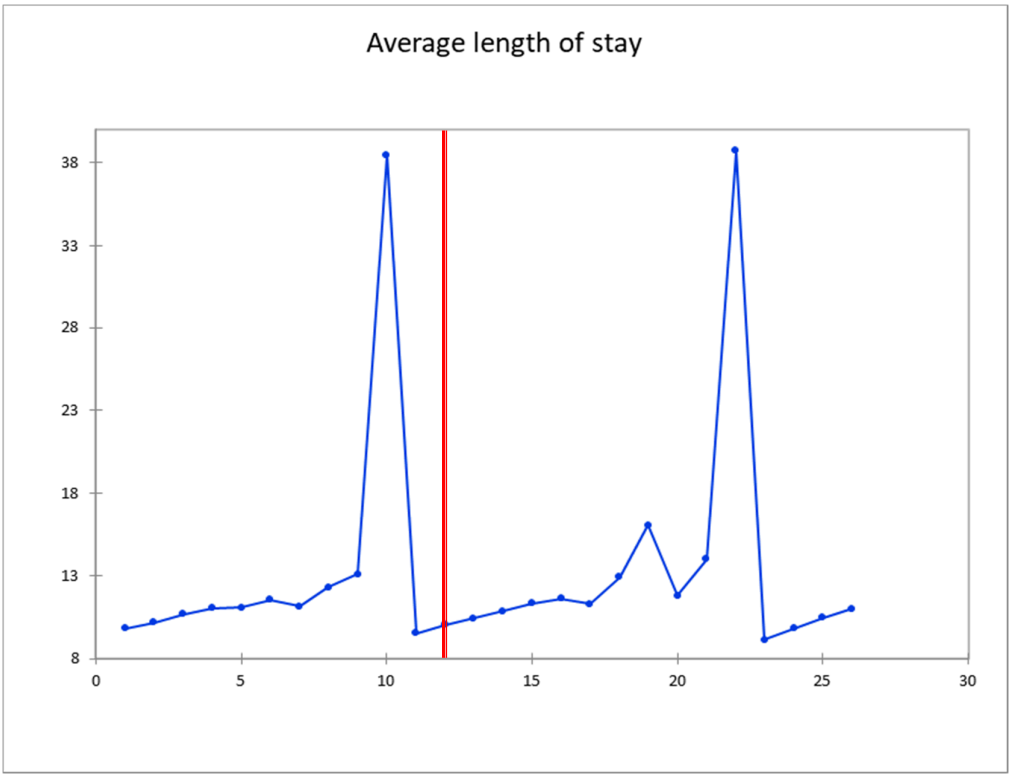
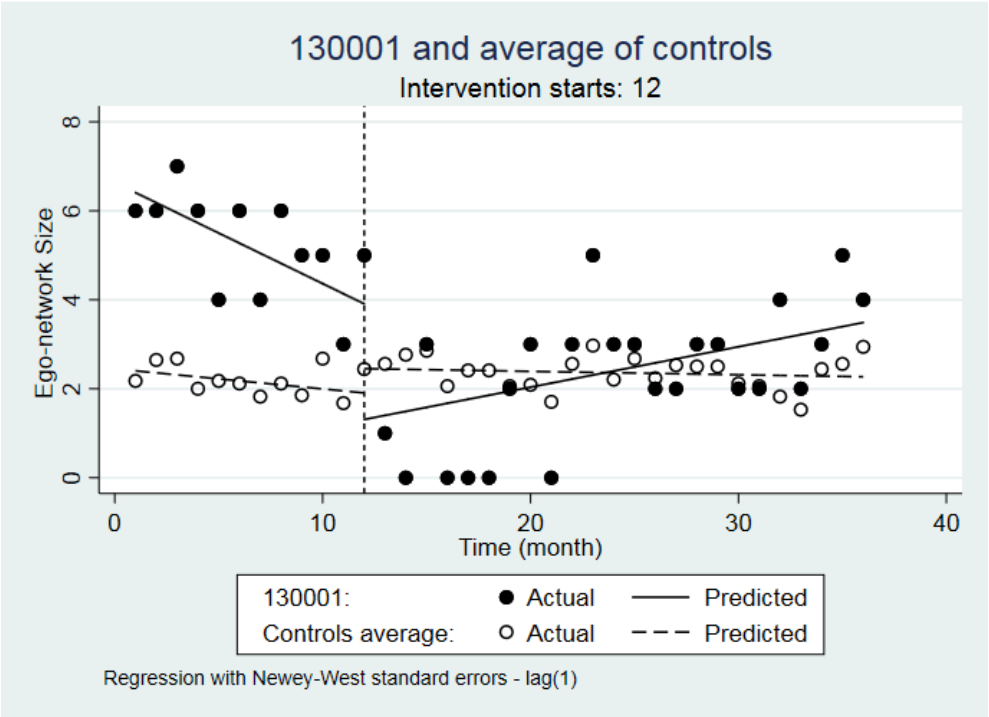
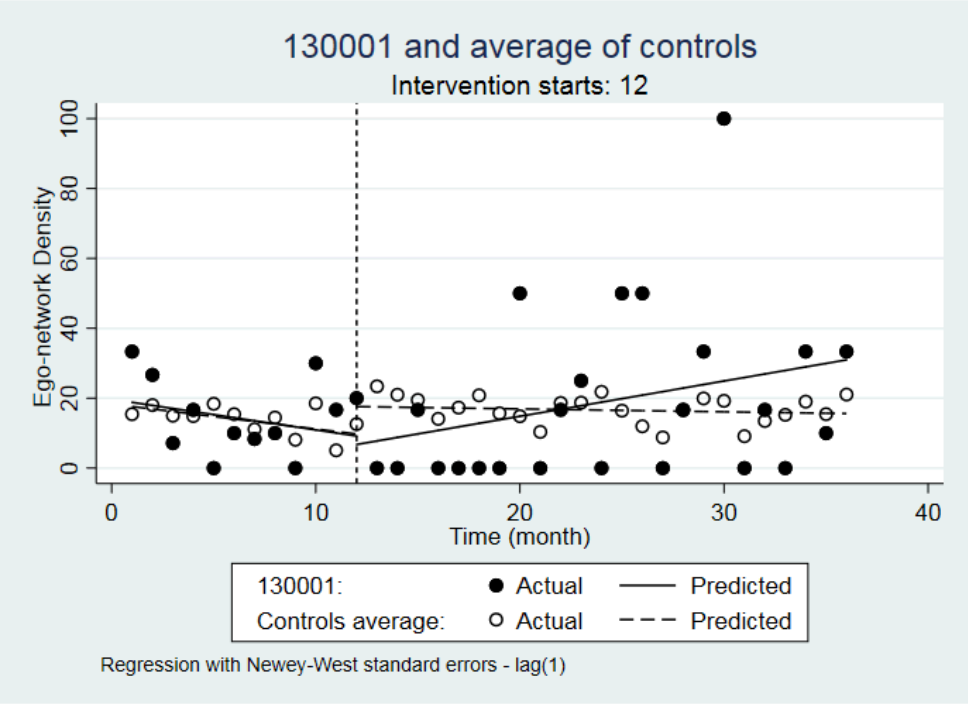
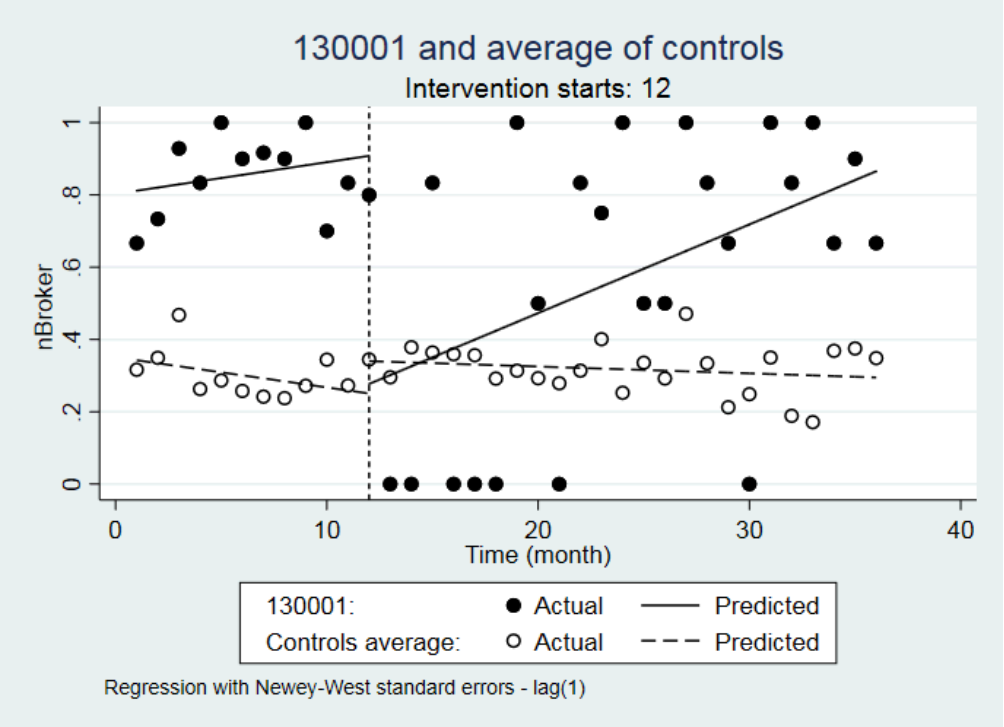
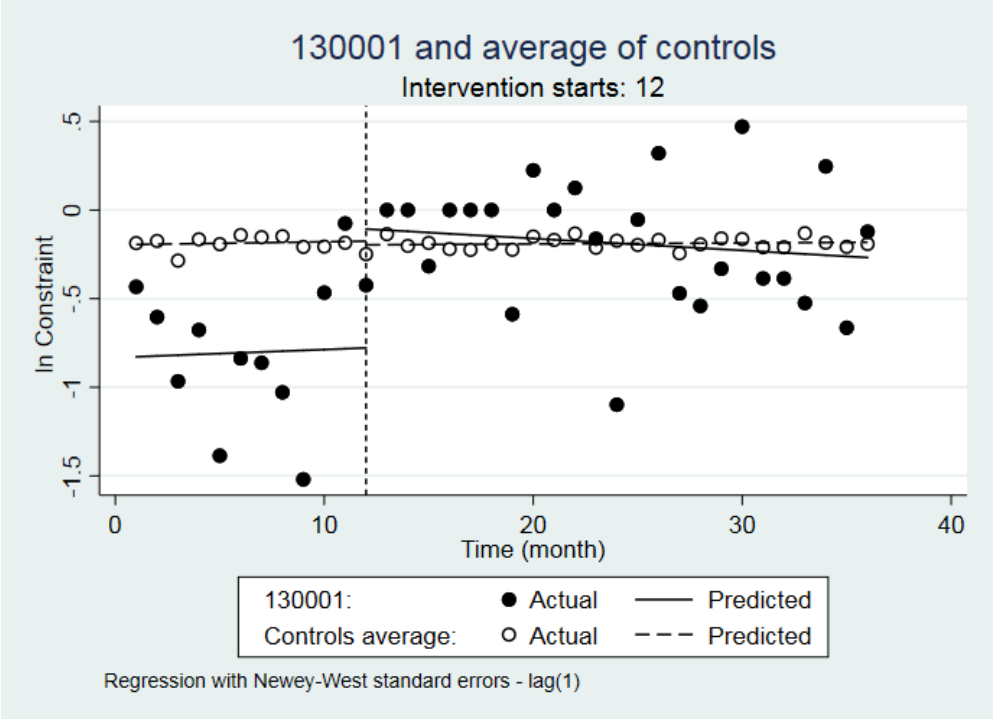


Figure 4a-4d: Plots of ITS regression results comparing hospital 130001 (dashed line) and other regional hospitals (continuous line), before and after the earthquake event.






130001 and average of controls
Intervention starts: 12
nBroker
0
.2
.4
.6
.8
1
0
10
20
30
40
Time (month)
130001:
Actual
Predicted
Controls average:
Actual
Predicted
Regression with Newey-West standard errors - lag(1)


130001 and average of controls
Intervention starts: 12
ln Constraint
-1.5
-1
-.5
0
.5
0
10
20
30
40
Time (month)
130001:
Actual
Predicted
Controls average:
Actual
Predicted
Regression with Newey-West standard errors - lag(1)