Mitigating ripple effect in supply networks:

The effect of trust and topology on resilience[1]

Ilaria Giannoccaro [a] and Anas Iftikhar[b]

[a]DMMM,Politecnico di Bari, Bari, Italy; [b]DSE, Università del Salento, Lecce, Italy

Abstract

The ripple effect refers to disruption propagation across the supply network affecting its global performance. To cope with it, supply networks should be resilient. This study investigates the drivers of supply network resilience, viewed as adaptive capacity to disruptions, focusing on trust and investigating the moderating role of network topology on the relationship between trust and resilience. We first develop an NK agent-based model of the supply network to simulate resilient performance. Then, a simulation analysis is carried out, to assess the effect of trust on the resilience of supply networks displaying different complex topologies. Our results confirm that trust positively affects supply network resilience; however, across the different topologies, the beneficial effect of trust varies. In particular, we find that trust is beneficial at most for the following topologies: local, small-world, block-diagonal, and random. For centralized, diagonal, and hierarchical topologies improving trust increases resilience at a moderate level. We also find that, as the frequency of disruptions rises, the positive effect of trust on resilience decreases. Managerial implications of the main findings are finally discussed.

Keywords: Resilience, trust, supply network topology, supply networks, agent-based simulation.

INTRODUCTION

To survive and succeed in the current competitive scenario characterized by frequent and unpredictable disruptive events from natural disasters, such as hurricanes or earthquakes, to terrorist attacks, human errors, and supply and market disruptions, supply networks should be designed to be resilient (Sutcliffe and Vogus, 2003; Craighead et al., 2007; Hendricks and Singhal, 2003; Kleindorfer and Saad, 2005; Svensson, 2000). Resilience is, in fact, the ability of a supply network as a whole to cope with perturbations, failures, and threats, by absorbing the disturbance and to quickly recover, so

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as to restore operations at earliest (Sheffi, 2005; Christopher and Peck, 2004; Ponomarov and Holcomb, 2009). It also involves the ability of supply network to face with and adapt to change occurring in the environment (Christopher and Peck, 2004). According to this perspective, resilience is thus related to dynamic capabilities such as flexibility, agility, and adaptive capacity.

Resilience is the proper strategy to deal with the ripple effect (Ivanov et al., 2014). The latter refers to disruption propagation towards supply chain stages. Ripple effect occurs when high impact and low-frequent events cascade downstream in the network and impact the firm's service level, revenues and profits (Dolgui et al., 2020; Ivanov and Dolgui, 2020; Kinra et al., 2019; Ojha et al., 2018; Simchi-Levi et al., 2015). The ripple effect impacts the structure of the supply network (Li et al., 2020; Hosseini et al., 2020; Dolgui et al., 2018) and can cause financial crisis (Kim et al., 2010). Resilient supply networks mitigate the negative effect of disruption propagation on network performance (Dolgui et al., 2018; Ivanov, 2018a, 2018b; Dolgui et al., 2020; Ivanov et al., 2019). Thus, to mitigate the ripple effect, resilient supply networks should be designed.

In this paper, we investigate this issue by conceptualizing supply network resilience according to a dynamic perspective as the capacity of the supply network to adapt to disturbance and secure a new desirable condition. In doing so, resilience is viewed as a complex adaptive system property resulting from spontaneous interactions of multiple interdependent actors. This is consistent with a research stream framing supply networks as complex adaptive systems (Choi et al., 2001; Surana et al., 2005; Pathak et al., 2007; Wycisk et al., 2008; Hearnshaw and Wilson 2013; Day, 2014; Giannoccaro, 2015; Giannoccaro et al., 2018).

It follows that to build resilient supply networks able to cope with the ripple effect, it is critical to enhance the adaptive capacity of supply networks. Borrowing from the theory on the antecedents of the adaptive capacity in complex adaptive systems (Rivkin and Siggelkow, 2007; Capaldo and Giannoccaro, 2015a), we focus on two variables, i.e. trust and topology, and analyze how they interact to affect supply network resilience.

Previous studies have shown that both trust and topology affect supply network resilience. In particular, trust among supply chain partners is identified as one of the most effective relational drivers of resilience, because it improves information sharing and collaboration among partnering firms and reduces the system vulnerability (Wieland and Wallenburg, 2013; Dubey et al., 2018; Hou et al., 2018). However, the extent to which trust improves the ability of the supply network to adapt to disruptions, by securing new desirable conditions, is an issue not properly investigated so far in the literature (Giannoccaro and Iftikhar, 2019). Overcoming this gap will permit to extend current knowledge about the beneficial effect of trust on resilience coherently with a dynamic conceptualization (i.e. resilience as adaptive capacity), rather than a static one (resilience as vulnerability). Note in fact that depending on the conceptualization, the effect of trust on supply network resilience could vary.

Similarly, the topology of the supply network is recognized as a critical factor affecting resilience, since the disruptive event propagates through the supply links. In fact, how firms are interconnected among each other is a critical source of the ripple effect (Ivanov, 2017; Dolgui et al., 2018; Liberatore et al., 2012). Some studies have investigated the direct effect of the supply network structure on resilience (Kim et al., 2015). We extend these works by investigating how trust interacts with the topology to affect supply network resilience. In doing so, we contribute to identifying in which structural conditions (i.e. topologies of supply networks) nurturing trust among partners is a valid strategy to enhance resilience. Based on previous studies concerning the influence of complex patterns on the system's adaptive capacity (Siggelkow and Rivkin, 2007), we expect that the benefits of trust on supply network resilience vary across the diverse topologies. By investigating this issue, we identify the supply network topologies for which undertaking trust-development initiatives may be more valuable. Based on our findings, we suggest managers of supply networks whether to invest in organizational mechanisms and tools to develop trust for improving supply network resilience.

As a research methodology, we adopt the NK simulation. Simulation is recognized as one of the most proper approaches to analyze the ripple effect in supply networks (Carvalho et al., 2012; Schmitt and Singh, 2012; Bueno-Solano and Cedillo-Campos, 2014; Ivanov et al., 2013, 2014; Ivanov et al., 2014; Garvey et al., 2015; Han and Shin, 2016; Mizgier, 2017; Sawik, 2017; Dolgui et al., 2018; Hosseini et al., 2020). Studies have adopted the following methodologies: system dynamics, agent-based modelling, discrete event simulation, graph theory-based simulation, and optimization-based simulation (Ivanov, 2017; Dolgui et al., 2018). We refer to the model based on the NK fitness simulation methodology, firstly developed by Capaldo and Giannoccaro (2015b). In this model, a supply network is conceived as made up of firms (agents) making operational decisions. The system dynamics spontaneously emerge over time from the decisions of the single agents, who follow specific rules, and from their interactions. This is coherent with an agent-based modeling approach (Bonabeau, 2002). The supply network exhibits ten different topologies and evolves in scenarios characterized by diverse levels of trust. However, the environment is static. We extend this model by introducing environments characterized by the existence of disruptions, occurring with a given frequency, and simulate the resilience in terms of the ability of the supply network to adapt to the negative event. In particular, after disruption occurred, the supply network adapts to change and reacts to the disturbance, to reach the same or better performance than those before the disruption. The averaged performance of the supply network overtime is defined as a measure of supply network resilience. A simulation analysis is carried out, aimed at investigating the effect of trust on the resilience of supply networks showing ten different topologies.

The remainder of this article is organized as follows. Section 2 reviews the literature on supply chain resilience. Section 3 presents the theoretical foundation of our conceptual model. Section 4 illustrates the NK model used to investigate the influence of trust and topology on supply network resilience. Then, Section 5 describes the simulation results and Section 6 discusses the theoretical and managerial implications. Conclusions are finally presented in Section 7.

2. LITERATURE REVIEW

2.1 Supply Chain Resilience

To date, there is no consensus on the definition of supply network resilience (Hohenstein et al., 2015; Kim et al., 2015). Researchers either adopt definitions as per the scope of their research or develop their own definition considering their research aim. Furthermore, some scholars define supply chain resilience referring to a single dimension (Brandon-Jones et al., 2014; Ambulkar et al., 2015; Gölgeci and Ponomarov, 2015; Liu and Lee, 2018), while others prefer multi-dimensional definitions (Zsidisin and Wagner, 2010). These dimensions mainly include robustness, flexibility, agility, and adaptability. In such a view, resilience is a multi-faceted capability of complex systems that encompasses avoiding, absorbing, adapting to and recovering from disruptions.

Focusing on definitions of supply network resilience, two main perspectives of resilience can be recognized, i.e. the static and dynamic ones (Rose, 2004; Annarelli and Nonino, 2016). The static perspective involves the ability of the supply network to absorb disturbance, maintaining its core operational functions when shocked (Bhamra et al., 2011). The dynamic perspective refers to the ability of the supply network to evolve over time reaching the original but even new, more favourable equilibrium state, adapting to disturbance (Carvalho et al., 2012). While the static perspective focuses on robustness and vulnerability, the dynamic perspective puts the attention on flexibility and adaptive capacity of the system, which is able to react to disturbance by changing its structure, processes, and functions, in order to increase its ability to persist in the environment thanks to flexibility, agility, and adaptability (Ivanov et al., 2013).

In this paper, we adopt the dynamic perspective and conceptualize supply network resilience as the ability of the entire supply network to adapt to disruption occurring in the environment, by securing a desirable system configuration. In such a view, the supply network does not necessarily return to the original state, as the desired state could be different in the new situation.

2.2 Classification of disruptions in supply networks

A supply network disruption is an unpredictable, unplanned and undesirable event, which affect normal supply network operations (Kleindorfer and Saad, 2005; Craighead et al., 2007; Hendricks and Singhal, 2003). Even though the ripple effect is usually related to low-frequency and high impact disruptions (Ivanov et al., 2014), in principle it can be caused by any type of disruption, as we describe next.

Disruptions can be classified according to several taxonomic criteria: 1) the severity of disruptions, 2) the likelihood of occurrence, 3) the place of disruption and 4) the nature of risks.

Severity distinguishes disruptions based on the magnitude of the event and includes the significance of consequences or impact (Norrman and Jansson, 2004; Tang, 2006; Harland et al., 2003). For example, events like a terrorist attack, labor or union strike, natural catastrophe are referred to as severe events or high-impact disruptions. Events pertaining to the daily operational matters, such as supplier non-conformance or shipment delay can be referred to as day-to-day disruptions (Kleindorfer and Saad, 2005; Huang et al., 2009) or low impact disruptions.

The likelihood of occurrence refers to the probability of happening of a specific event. Usually, events that are severe or possess high impact have less probability to occur; whereas, events that are less severe or possess low impact have a high probability to occur. In the extant literature, the severity and the likelihood of the event are classified as *high likelihood, low impact disruptions* and *low likelihood, high impact disruptions* (Ellis et al., 2010).

Place of disruption is the common form for risk classification. The disturbance may plague the supply chain at different locations. Christopher and Peck (2004) have classified this category into three classes: i) internal to the firm, ii) external to the firm and internal to supply chain network, and iii) external to the network.

Risks are also classified as per their *nature*. Nature of risks is associated with the location of the source of disruption. *Process risks* and *control risks* refer to sources of disruptions internal to the firm, *demand* and *supply risks* refer to sources external to the firm, and *environmental risks* concern to sources external to the network (Christopher and Peck, 2004).

2.3 Drivers of supply network resilience

Supply network resilience is affected by multiple drivers. We classify them into three classes: 1) structural features, 2) operational strategies, and 3) relational variables. Structural features refer to the physical structure of the supply network. They include network topology, density, complexity, node criticality, and geographical sourcing diversification (Craighead et al., 2007; Falasca et al., 2008; Blackhurst et al., 2011; Shao, 2013; Ivanov et al., 2014; Brandon-Jones et al., 2014; Cardoso et al., 2015; Kim et al., 2015; Scheibe and Blackhurst, 2019; Hosseini et al., 2020). Operational features refer to supply strategies, such as multiple sourcing, postponement, safety stocks (Sheffi, 2005; Tang, 2006; Tomlin, 2006; Sodhi and Lee, 2007; Tang and Tomlin, 2008; Knemeyer et al., 2009; Yang and Yang, 2010; Colicchia et al., 2010; Ivanov et al., 2016; Lee and Rha, 2016; Brusset and Teller, 2017; Zineb et al., 2017; Dolgui et al., 2018). Finally, relational features mainly refer to collaboration, trust, and information sharing (Christopher and Peck, 2004; Datta et al., 2007; Wieland and Wallenburg, 2013; Riley et al., 2016; Mandal et al., 2016; Durach et al., 2018; Dubey et al., 2018; Verghese et al., 2019; Ivanov et al., 2019). We discuss the drivers for each class in more details below.

2.3.1 Structural Features

Structural features refer to variables describing the physical structure of the supply network. They are usually characterized by using complex systems measures, such as network topology, density, complexity, node criticality, geographical sourcing diversification (Craighead et al., 2007; Falasca et al., 2008; Blackhurst et al., 2011; Brandon-Jones et al., 2014; Ivanov et al., 2014; Cardoso et al., 2015).

Network topology is described by referring to the patterns of complex networks. For example, Thadakamalla et al. (2004) analyze the resilience of a military supply network adopting a preferential attachment pattern. Kim et al. (2015) investigate the resilience of complex networks adopting a block diagonal, scale-free, centralized, and diagonal patterns. They find that the scale-free network characterized by a power-law node degree distribution is associated with the highest resilience to disruptions occurring at the node level. Mari et al. (2015) design a resilient supply chain network from the complex network topology perspective. They develop a resilient supply chain growth model. Their model is found to be more resilient than the scale-free one. Finally, Li et al. (2017) find that network topology has a significant influence on the supply network resilience.

Resilience also depends on the *density* of the network. A supply network is highly dense when a large number of nodes are closely clustered together or it is loosely dense when the nodes are clustered largely away from each other. High-density is associated with proximity to the partners in the supply network and vice versa. Falasca et al. (2008) measure and study the relationship between density and the overall resilience of the supply chain by developing a simulation model. They find that the higher the density of the supply network, the more severe the impact of supply chain disruptions is.

Resilience in the supply network is also affected by the *complexity* level of the network (Falasca et al., 2008; Craighead et al., 2007). Supply chain complexity level determines the severity of disruptions in the network as it refers to the number of nodes and the interconnections between those nodes in the network. The interconnection between nodes represents the material flow from an upstream node to the downstream node, return flow from downstream to upstream, and the transfer flow between the nodes at the same tier level. Even though with some exceptions, generally, the higher the complexity of the supply network, the more significant the impact of supply disruptions is. In a highly complex environment, due to the interdependencies, any disruption at any node can potentially pass on the disruption effect to other nodes.

Node criticality is a further source for contributing to supply network disruptions. Craighead et al. (2007) define node criticality as the significance of a single node or set of nodes in the entire supply network. In the supply network, every node is responsible for contributing some value. Some nodes are more critical than others because of their significant contribution. For example, the supplier of very critical material in any industry, who is also the sole supplier of many firms, represents the critical node in the supply network. Therefore, any disruption occurring at this node will have an escalating effect in the supply network compared to that at the less critical node. Sokolov et al. (2016) quantify the ripple effect of the supply chain from the network structure perspective. In this study, a multi-criteria decision-making model based on AHP is proposed to select a stable and resilient supply chain design structure.

2.3.2 Operational strategies

Antecedents belonging to the operational strategies class refer to operations management policies increasing agility, flexibility, and reducing vulnerability. Useful strategies to this end are maintaining extra inventory, multiple sourcing policy instead of sole sourcing, and postponement (Costantino et al., 2012; Chopra and Sodhi, 2014; Varas et al., 2018; Wang and Yin, 2018).

Bundschuh et al. (2006), Tomlin (2006) and Feng and Shi (2012) suggest adopting multiple sourcing strategies for catering demand needs, during material shortages at disruption times. Quite often, multiple sourcing is practised in the case of non-conformities or supplier unreliability. Namdar et al. (2017) investigate the use of sourcing strategies to achieve supply chain resilience under disruptions by comparing single and multiple sourcing.

Maintaining a backup facility to cope with disruptions is one of the most popular strategies being discussed in the extant literature and also one of the most practised strategies (Chopra et al., 2007;

Dada et al., 2007). Tang (2006) focuses on maintaining redundant inventories in warehouses and postponing the demands for disruption management. With the help of backup facilities, firms can cover themselves by continuing the production process in the face of disruptions. Similarly, Kamalahmadi and Parast (2016) mention strategies including multiple sourcing, maintaining buffer stocks, overcapacity, and backup suppliers in the supply base. Multiple sourcing and safety stock strategies are referred to as preventive measures by Hohenstein et al. (2015) to avoid disruptions and ensure resilience. Dolgui et al. (2018) argue that flexibility is a system's ability, which could bring change in process and structure to avoid disturbances, as it pertains to the re-allocation of redundant inventories and capacities in the network.

Recent studies have shown that postponement strategies mitigate disruption risks associated with supply disruptions (Gualandris and Kalchschmidt, 2015) and demand uncertainty (Choi et al., 2017). Earlier studies have also found postponement as a flexibility enabler useful for reducing disruption risks (Tang and Tomlin, 2008; Paul et al., 2017).

2.3.3 Relational Features

Relational features refer to dimensions of relational governance. They mainly involve the following variables: information sharing, collaboration, and trust.

In a dynamic supply network, *sharing of right information* has a pivotal role in affecting resilience since it positively influences the efficacy of the relationships among supply network partners (Holweg and Pil, 2008). Furthermore, information is critical to make effective supply chain decisions. Organizations that are forecast-driven are bound to take decisions in isolation from other members in the network. This lack of sharing information is a major source of vulnerability (Christopher and Peck, 2004). By communicating with participants in the supply network, information about potential development across the network could be obtained. Communication among partners possesses the capability to enhance visibility and speed, which has a positive impact on resilience (Wieland and

Wallenburg, 2013). Furthermore, Jain et al (2017) have considered information sharing as a substantial and vital element for enabling resilience and showed it reinforces the positive effects of different variables. Mandal (2012) suggests that sharing of relevant information improves collaboration, which in turn positively influences resilience. Ivanov et al. (2019) argue that digital technologies offer visibility in the supply chain, which further plays a key role in managing disruption risk and ripple effect in the supply chain.

Collaboration is when two or more autonomous companies working jointly to achieve strategic objectives (Pettit et al., 2010). Collaboration is required for having effective risk management across the supply chain. This is more needed when the supply network is characterized by high density (Kamalahmadi and Parsat, 2016) and when lead times are long (Sheffi, 2005). Wieland and Wallenburg (2013) find that cooperation with communication has a positive effect on resilience. Collaboration positively affects the market sensitiveness and market sensitiveness in turn influences risk management culture (Jain et al., 2017). Bakshi and Kleindorfer (2009) demonstrate that firms having cooperative contracts among the supply chain partners show high significance of investment in supply chain resilience.

The concept of *trust* is a major topic in the supply chain literature (Johnston et al., 2004). Trust represents the willingness among the participants in the network to cooperate, collaborate and share the right information without any fear of loss. Faisal et al. (2007) state that trust provides an opportunity to cooperate and collaborate within the organization and across firms in the supply network. According to Sinha et al. (2004), the main cause that leads towards risks in supply chains is the lack of trust. Wicher and Lenort (2012) have analyzed a network where the participants have a tendency to trust each other, where they freely share their problems and challenges. They show that cooperative relationships emerged from trust promote resilience. Soni et al. (2014) rank trust as the most important enabler of supply chain resilience out of fourteen drivers. Similarly, Dubey et al.

(2018) argue that the existence of trust and commitment within the supply chain stakeholders improves cooperation and, hence, it results in resilient supply chains.

3. THEORY

3.1 The relationship between trust and resilience in supply networks

Trust in supply network is defined as an expected collaboration among partnering firms, which will do what is better for the overall network, even when collaboration may lead to a local disadvantage (Zaheer et al., 1998; Rousseau et al., 1998; McCarter and Northcraft, 2007). Trusting firms collaborate because they trust that their partners will behave in the interest of the overall system and will not adopt any opportunistic behaviours (Barney and Hansen, 1994; Bradach and Eccles, 1989; Lai et al., 2012). In case of trust, firms in the supply network behave in the best interest of the entire supply network, to increase its global performance, even when this is locally detrimental for them. Trust existence ensures that neither of the partners adopts opportunistic behaviour even for short term benefits and this attitude will lead towards the stability of firms for a long term period (Chiles and McMackin, 1996). Wu (2011) has considered trust as a means to reduce uncertainty and risks because it is capable to maintain successful relationships in the network. Trust is considered as an essential element for building collaborative and strategic alliances (Wallenburg et al., 2011).

In recent studies, trust has been demonstrated to directly affect the adaptive capacity of a supply network (Capaldo and Giannoccaro, 2015b). When trust is widespread in the supply network, firms are able to select and identify solutions better fitting with the environment, because they prefer to improve global performance rather than achieve local improvement. It follows that trust should play a direct role in improving resilience, defined as the ability to adapt to the negative event. Once disruption occurred, supply networks characterized by high trust relationships should be able to better adapt and find better desirable conditions than supply networks characterized by low trustworthy relationships. We intend to investigate this relationship between trust and resilience.

3.2 The role of network topology on the resilience of the supply networks

Supply network topology refers to the pattern of connections among the firms in the supply network. Due to these connections, firms depend upon one another for product and process accomplishments and for their respective resources and knowledge. A useful approach to analyze supply network topology is to adopt the theory of complex systems. In particular, Rivkin and Siggelkow (2007) identify ten complex patterns, i.e., random, local, small-world, block-diagonal, preferential attachment, scale-free, hierarchical, diagonal, centralized, and dependent.

Recent studies have shown that real supply chain networks exhibit these complex network topologies (Capaldo and Giannoccaro, 2015a; 2015b; Kim et al., 2015). In the *random* pattern, interactions occur on a random basis and most nodes will have approximately the same number of links, while very few nodes will show a considerably lower or higher number of links than the average (Erdos and Renyi, 1959). This topology is shown by supply networks where connections are arranged so that each member firm is affected by approximately the same number of other firms. Accordingly, this pattern arises in supply chains composed of predominantly micro-small firms wherein, in order to fully fulfill customer orders that typically exceed the internal capacity of every single assembler, orders are split among several assemblers (Albino et al., 2007). The *local* topology is characterized by connections occurring only between adjacent nodes positioned in a regular lattice. Nodes are thus assumed to lie on a "ring", where each node is affected by both the node that precedes it and the node that follows it. This topology may be exhibited by supply networks adopting just in time strategies, as this pattern portrays a chain of repeated relationships between supplier and customer. Here each member firm buys from the upstream node and supplies to the downstream node, so that each firm is directly linked with the adjacent ones, both upstream and downstream. The *small-world* pattern is a variant of the local one, where most connections occur among adjacent nodes, while a few remaining connections exist between more distant nodes (Watts, 1999). This pattern property is found in alliance networks

in manufacturing industries (Schilling and Phelps, 2007) as well as in the Indian railway network (Sen et al., 2003). The *block-diagonal* pattern is characterized by clustered connections among nodes, i.e., they occur only inside blocks (i.e., modules or communities) and not between different blocks. This pattern characterizes supply chains producing and distributing modular product and services. In the *preferential attachment* topology, the nodes attach preferentially to other nodes having a large number of connections (Barabasi and Albert, 1999). This pattern may correspond to the case of a small number of core manufacturers or assemblers with a large number of peripheral affiliated suppliers, such as in the case of a vertical keiretsu supply network. When the node distribution connectivity follows a power law, the network topology is *scale-free* (Barabasi and Albert, 1999).
The scale-free pattern is shown by the hub and spoke networks, such as the distribution/transportation systems (O'Kelly, 1998), the airline networks (Bryan and O'Kelly, 1999), and the Indian auto component industry (Parhi, 2005). The scale-free pattern may also resemble the underlying network structure of supply chains in industrial districts, where larger firms play the leading role and organize production among groups of smaller subcontractors. The *hierarchical* pattern assumes that nodes are hierarchically ordered and that each node may influence only those with lower ranks. The *diagonal* pattern is similar, except that the node 1 is not the most influential, as occurs in the hierarchical pattern. The *hierarchical* and *diagonal pattern* may arise in multi-tier supply networks where the leading firm in the supply chain network outsources their supply side, i.e. delegates their first-tier suppliers the responsibility to coordinate and manage sub-suppliers. This is the case for several OEMs in the automotive industry, who directly select and manage their first-tier suppliers while delegating to their first-tier and second-tier suppliers the tasks of selecting and managing larger numbers of second-tier and third-tier suppliers, respectively (e.g., Choi and Hong, 2002).

The *centralized* and *dependent* are specular. In the centralized pattern, a few nodes influenced all the others, which in turn have no other direct connections. It occurs in supply chain networks where inventories are managed by a central actor, such as when Vendor-Managed Inventory or Continuous Replenishment agreements are adopted. Under these agreements, inventory management is indeed centralized by manufacturers who manage the inventories of retailers by making decisions concerning replenishment time and order quantity. Other examples of the centralized interaction pattern are convergent supply chains, used for assembling several types of products (e.g., household electrical appliances), where the assembler makes production planning decisions that affect all the suppliers, whose decisions, in turn, have little influence within the network.

Conversely, in the dependent pattern, a few nodes are affected by all the others, while not exerting any influence themselves. This happens, for example, in supply chains using postponement strategies, where product differentiation is delayed at the distribution stage so that standard not-customized products are produced in several manufacturing sites and then shipped to a few regional warehouses for customization according to the users' needs and requirements. Similarly, the dependent pattern characterizes distribution supply chains composed of a few large warehouses serving numerous independent retailers. In such conditions, the retailers' decisions (i.e., orders) influence the warehouses' requirement planning decisions, which in turn have slight or no influence on the retailers' decisions.

A further finding of the literature on complex networks is that the adaptive capacity of a complex network is influenced by its topology (Rivkin and Siggelkow, 2007). Based on the above, it follows that the topology of the supply network, characterized using the complex pattern, plays a critical role in affecting its resilience. Furthermore, we argue that the topology of the supply network influences the relationship between trust and resilience. Inducing partnering firms to behave altruistically in the best interest of the entire supply network, even when this is locally detrimental for them, could improve the adaptive capacity of the system only in the case of specific patterns of connections and not for any type of topology. In fact, the improvement of adaptive capacity of the system thanks to high trust levels can differ across the different supply network topologies.

4. METHODOLOGY

In this study, we frame the supply network as a complex adaptive system and adopt the NK fitness landscape methodology to model and simulate their behaviour.

4.1 NK Model of a supply network

The NK fitness landscape model is a simulation approach firstly developed by Kauffman (1993) to study the evolution of biological systems. Later this approach was adopted in the organizational and management studies for modelling strategic decisions in firms and supply chain contexts (Levinthal, 1997; McKelvey, 1999; Rivkin, 2001; Siggelkow, 2001; Aggarwal et al., 2011; Giannoccaro, 2011; 2015; Capaldo and Giannoccaro, 2015b; Giannoccaro et al., 2018; Giannoccaro, 2018).

We refer to the model developed by Capaldo and Giannoccaro (2015b). This model reproduces the supply network adaptive behaviors and simulates supply network performance in scenarios characterized by presence and absence of trust among firms in static and complex environments.

In the following, we summarize the main features of the model and then we describe how we extend it both to reproduce environments characterized by disruptions and to compute the resilient performance of the supply network.

The supply network is made up of N agents (firms), making decisions on how to accomplish their main operational activities, such as the transportation mode, the safety stock, the order quantity, and so on. The firms are interconnected one with each other according to ten possible different topologies, Each topology is modelled by means of an influence matrix, where any x in (*i*,*j*) cell means that the firm *i* is influenced by the firm *j*, i.e., firm *i* depends on firm *j*.

Each agent makes the decision following specific rules and the system behaviour spontaneously emerges from their actions. The adaptive process is modelled as an adaptive walk on the performance landscape, in search of the configuration with the highest performance (global peak). The performance landscape, which maps the configurations into the attendant payoffs, is generated by following the classical NK procedure (Kaufmann, 1993), as we described in the next paragraph.

In particular, an N-digit string represents a specific set of choices made by the firms on the considered decisions (choice configuration) $\mathbf{d} = (d_1, d_2, \ldots, d_N)$, with $d_i = 0$ *or* 1 ($i = 1,\ldots N$), and models the supply network configuration. Each decision d_i contributes to the overall supply network payoff, where C_i is the contribution drawn at random from a uniform [0,1] distribution. Note that the contribution C_i depends not only on the choice on the decision d_i itself but also on how the interacting decisions are chosen. This implies that each topology corresponds to a different shape of the performance landscape.

The overall payoff in a given configuration **d** is computed by averaging the contributions C_i on the N decisions ($P_{SC}(\mathbf{d}) = \left[\sum_{i=1}^{N} C_i(d)\right] / N$). Assuming that each firm *i* makes one decision d_i, the payoff of the firm *i* is given by the contribution C_i ($P_i(\boldsymbol{d}) = C_i(\boldsymbol{d})$). Note that the single contributions C_i stand for the local performance of the individual firms ($P_i(\mathbf{d})$), while the overall payoff $P_{SC}(\mathbf{d})$ corresponds to the supply network performance. Therefore, for each considered topology, the corresponding landscape conveys information about the performance of each single firm (P_i) and the total supply chain performance (P_{sc}) in all the possible combinations of decisions made by the firms *i*.

Note that the proposed NK fitness landscape model takes into account the ripple effect by means of the influence matrix modelling the supply network topology (i.e. the landscape) and coherently with a conceptualization of the resilience as adaptive capacity. Depending on the interconnections among firms (topology), a disruption differently impacts the supply network performance because of the different ability of supply network to adapt to the negative event. Therefore, the disruption affects the supply network in different ways depending on the topology and results in different performance outcome.

4.1.1 The procedure to generate the NK fitness landscape

To generate the NK landscape, first, the value of N and K is fixed and the influence matrix recording interactions among decisions is settled.

Successively, the contribution of each decision d_i to the total payoff, C_i, is generated drawing at random from a uniform distribution U[0,1]. Then, the payoff of each configuration is calculated by using the formula:

$$P(\boldsymbol{d}) = \left(\sum_{i=1}^{N} C_i(\boldsymbol{d})\right)/N \qquad (1)$$

To generate C_i, note that it is affected by the choices on decision d_i itself but also on the interdependent decisions. For example, let's consider that d_1 interacts with d_2. This means that the contribution of d_1 is also affected by how d_2 is resolved. As a result, C_1 is the same in all the choice configurations where d_1 and d_2 assume the same value, while when d_1 or d_2 changes, a different C_1 is assigned.

An exemplar NK landscape is given in Figure 1 corresponding to the case of N=3, K=2, and the influence matrix shown. Given that d_1 depends on d_2, C_1 assumes four different values, drawn at random from the uniform distribution U[0,1]. The configurations that assume the same value are those sharing the same d_1 and d_2, i.e. *a* and *b* (0.12), *c* and *g* (0.57), *d* and *f* (0.54), *e* and *h* (0.41).

	Choice configuration			C_1	C_2	C_3	P(d)
ID	**d1**	**d2**	**d3**				
a	0	0	0	0.12	0.29	0.96	0.46
b	0	0	1	0.12	0.65	0.16	0.31
c	0	1	0	0.57	0.76	0.96	**0.76**
d	1	0	0	0.54	0.29	0.14	0.32
e	1	1	0	0.41	0.76	0.14	0.44
f	1	0	1	0.54	0.65	0.89	0.69
g	0	1	1	0.57	0.59	0.16	0.44
h	1	1	1	0.41	0.59	0.89	0.63

	d1	**d2**	**d3**
d1	x	x	
d2		x	x
d3	x		x

Figure 1. Exemplar landscape.

4.2 The model of the environment with disruptions

We modify the model proposed by Capaldo and Giannoccaro (2015b) to introduce disruptions in the environment. To do so, we model the outcome of the disruption (i.e. the impact of the disruption on the supply network performance), rather than the triggering event (e.g. an incident). Coherently, the disturbance is modelled as an event that modifies the NK fitness landscape, i.e. the contributions C_i. In particular, when disruption in the environment occured, the supply network performance decreases and the selected configuration is no more beneficial. A new supply network configuration should be thus identified to improve performance. This modeling strategy is also consistent with previous studies that model disruptions using the NK approach (Giannoccaro et al., 2018).

The disruption may occur with different frequency. Even though literature has mainly analyzed the resilience when a single negative event occurs, it is common that disruptions happen recurrently (Bode and Wagner, 2015). Thus, we model the frequency of disturbance by introducing the parameter (Δ), i.e. the time arising between two subsequent disruptive events in time steps. The higher the frequency, the higher the number of disruptions. We consider three increasing frequencies values.

We model environmental disruptions by generating new landscapes during the simulation process at each Δ step of the simulation time. This means that the environment stays fixed for $\Delta-1$ steps, then changes and maintains the same value for other $\Delta-1$ steps, and so on. The longer Δ, the more stable the environment. In particular, at each Δ step, a new landscape is generated with a correlation with the previous one. The new contribution C_i is computed with the following formula:

$$C_i(\boldsymbol{d}) = \tau\, C_{i\,\mathrm{old}} + (1 - \tau)\, u\,, \qquad (2)$$

where u is drawn at random from a uniform [0,1] distribution and $\tau = 0.2$ (Rivkin and Siggelkow, 2005).

Once the change in the fitness landscape has taken place, the system tries to discover new configurations which offer higher payoff, i.e. tries to adapt to the disruption.

This search process is affected by the trust as described in the following paragraph.

4.3 The algorithm modelling the level of trust

We use the search algorithm proposed by Capaldo and Giannoccaro (2015b) to model the level of trust. In the presence of a high level of trust, firms (i.e. agents) decide to adopt a new configuration if this is beneficial for the entire supply network (i.e., P_{SC} rises), regardless of the impact that such change exerts on its individual performance. Decreasing the level of trust, firms (agents) can accept deteriorating local performance (P_i) for the increase of the supply network performance, only to a certain degree (β = 1- *TRUST*). In absence of trust, the new configuration is acceptable only if this permits to increase the local firm payoff.

To summarize, the evolution process of the supply network spontaneously emerges by the accomplishment of the following steps:

a) An agent *i* at random changes its decision d_i

b) The new supply network configuration $\boldsymbol{v}_{\mathbf{new}}$ is computed

c) The supply network payoff $P_{SC}(\boldsymbol{v}_{\boldsymbol{new}})$ and the local payoffs of all the supply network agents $P_i(\boldsymbol{v}_{\boldsymbol{new}})$ corresponding to the new supply network configuration are computed;

d) The agent accepts the change in the decision, so that the system moves into the new configuration, if:

$P_{SC}(v_{\text{new}}) > P_{SC}(v_{\text{status quo}})$ and $P_i(v_{\text{new}}) > (1- TRUST)\ P_i(v_{\text{status quo}})$,

Otherwise, the agent does not accept the change in the decision and the system maintains status quo configuration;

e) Steps a-d are repeated for a given number of times (i.e., simulation runs).

We model three trust levels, i.e. 1, 0.5, and 0. When *TRUST* = 1 the supply network is characterized by a high trust, with *TRUST* = 0.5 the supply network has a low level of trust, whereas when *TRUST*

= 0 the supply network is not trustworthy, because the system moves into a beneficial configuration only if this determines also an improvement of the local firm payoff.

4.4 The resilience measurement

We measure resilience by capturing the ability of the supply network to adapt to disturbance and identify new desirable configurations characterized by high supply network payoff.

Then, we compute the resilience of supply network by averaging the payoff of the whole supply network over the entire simulation period (*AverageP*). The higher the average performance, the higher the supply network resilience. This measure is coherent with a dynamic conceptualization of resilience, which focuses on the ability of the system to reach a new desirable configuration after that a disturbance occurred, which could be also better than the original one.

5. SIMULATION ANALYSIS

We carried out a simulation analysis to compare the resilience of supply networks characterized by different topologies and three different levels of trust (high, low, no). In particular, we simulate 10 topologies: block-diagonal, centralized, dependent, random, local, hierarchical, scale-free, preferential attachment, small-world, and diagonal. We generate the landscape by setting N = 12 and K = 3. These values assure the main phenomena under investigation (i.e. the influence of topology) to be reproduced, avoiding at the same time high computational effort. A similar set is found in Rivkin and Siggelkow (2007) and Capaldo and Giannoccaro (2015a; 2015b). The influence matrices of the ten supply network topologies are given in Appendix A.

Simulation time is set to 200 steps consistently with Siggelkow and Rivkin (2005) and Capaldo and Giannoccaro (2015b), enough long to guarantee the adaptation of the system in any circumstance and to distinguish increasing frequencies of disturbance (low, medium, high). Since landscapes are generated according to a stochastic procedure, to guarantee the validity of results, each type of landscape is generated 300 times. Then, the simulation is replicated on each landscape and the average and the standard deviation of the resilience performance computed. For each considered landscape, the simulation was carried out for three values of trust, i.e. high level of trust, low level of trust, and absence of trust. In total, we simulated a plan of experiments made up of 120 scenarios (10x3x4).

5.1 Results

Results of simulations are shown in Table 1. Resilient performance is reported for each topology, level of trust, and frequency of disruption. The performance difference between the scenario with high trust and absence of trust is also computed, in percentage to the case of high trust (Diff%).

Table 1. Resilient performance of supply networks (K=3).*

	Trust					Trust			
	High	**Low**	**No**	**Diff****		**High**	**Low**	**No**	**Diff****
BLOCK-DIAGONAL					**LOCAL**				
Δ=40	0.8749	0.8688	0.8451	***3.53%***	Δ=40	0.8727	0.8631	0.8338	***4.67%***
Δ=20	0.8513	0.8439	0.8232	***3.41%***	Δ=20	0.8420	0.8347	0.8124	***3.64%***
Δ=10	0.8183	0.8152	0.7966	***2.72%***	Δ=10	0.8094	0.8043	0.7847	***3.15%***
Mean	**0.8483**	**0.8426**	**0.8216**	***3.25%***	***Mean***	**0.8414**	**0.8340**	**0.8103**	***3.84%***
CENTRALIZED					**DEPENDENT**				
Δ=40	0.8861	0.8783	0.8644	***2.51%***	Δ=40	0.8529	0.8539	0.8523	***0.07%***
Δ=20	0.8550	0.8509	0.8395	***1.85%***	Δ=20	0.8369	0.8386	0.8329	***0.48%***
Δ=10	0.8232	0.8212	0.8116	***1.43%***	Δ=10	0.8164	0.8173	0.8129	***0.43%***
Mean	**0.8548**	**0.8501**	**0.8385**	***1.94%***	***Mean***	**0.8354**	**0.8366**	**0.8327**	***0.32%***
DIAGONAL					**HIERARCHICAL**				
Δ=40	0.8734	0.8784	0.8585	***1.74%***	Δ=40	0.8802	0.8802	0.8667	***1.56%***
Δ=20	0.8537	0.8509	0.8373	***1.96%***	Δ=20	0.8533	0.8521	0.8404	***1.53%***
Δ=10	0.8324	0.8213	0.8192	***1.61%***	Δ=10	0.8256	0.8218	0.813	***1.55%***
Mean	**0.8532**	**0.8502**	**0.8383**	***1.78%***	***Mean***	**0.8530**	**0.8514**	**0.8400**	***1.55%***
RANDOM					**SMALL WORLD**				
Δ=40	0.8584	0.8546	0.8271	***3.78%***	Δ=40	0.8705	0.8598	0.8369	***4.01%***
Δ=20	0.8271	0.8209	0.8	***3.39%***	Δ=20	0.8411	0.8317	0.8099	***3.85%***
Δ=10	0.796	0.7901	0.7738	***2.87%***	Δ=10	0.8073	0.803	0.7845	***2.91%***
Mean	**0.8272**	**0.8219**	**0.8003**	***3.36%***	***Mean***	**0.8396**	**0.8315**	**0.8104**	***3.60%***
SCALE-FREE					**PREFERENTIAL ATTACHMENT**				
Δ=40	0.8855	0.8767	0.8598	***2.99%***	Δ=40	0.8805	0.8725	0.8489	***3.72%***
Δ=20	0.8648	0.8582	0.8423	***2.67%***	Δ=20	0.8585	0.8525	0.8373	***2.53%***
Δ=10	0.8427	0.8369	0.8239	***2.28%***	Δ=10	0.8362	0.832	0.8177	***2.26%***
Mean	**0.8643**	**0.8573**	**0.8420**	***2.65%***	***Mean***	**0.8584**	**0.8523**	**0.8346**	***2.85%***

*Standard deviation are given in Appendix B. All differences are significant by performing t test.**Diff = (High-No)/High

Table 2 shows the results achieved by averaging resilient performance across topologies, fixed the frequency of disturbance and the level of trust. We also computed the performance difference between supply networks characterized by a high level of trust and no level of trust (in percentage to high trust). Note that the performance difference is always positive. These findings clearly show that supply networks with high levels of trust achieve higher resilience than supply networks with a low/no level of trust. Hence, trust has a direct positive effect on the supply network adaptive capacity, thereby positively affecting its resilience.

The findings in Table 2 also show that the frequency of disruptions negatively affects the relationship between trust and resilience. In fact, the performance difference shows an increase of about 2.76%, 2.46%, and 2.06%, in the case of low (Δ=40), medium (Δ=20), and high (Δ=10) frequency of disruptions, respectively (last column in Table 3). The higher the number of disruptions occurred, the lower the beneficial effect of trust for supply network resilience. Since trust improves the adaptive capacity of the system, this is more beneficial when there is more time to adapt.

Table 2. Average supply network performance.

		Trust		**Difference**
Frequency	**High**	**Low**	**No**	**(High - No)/High**
Δ=40	0.87351	0.86862	0.84937	2.76%
Δ=20	0.84837	0.84346	0.82752	2.46%
Δ=10	0.82074	0.8163	0.80380	2.06%
Mean	***0.86094***	***0.85604***	***0.83844***	**2.61%**

Our results also show that the relationship between trust and resilience is moderated by the network topology. Looking at the performance difference between high and no trust in percentage to high trust in Table 1, we note that the values vary across topologies. The performance difference ranges from 0.32% in the case of a dependent structure to 3.84% in the case of a local structure. Trust is beneficial at most for the following topologies: local, small-world, block-diagonal, and random. For centralized, diagonal, and hierarchical topologies improving trust increases resilience only at a moderate level. In the case of a supply network showing a dependent topology, the beneficial effect of trust on resilience is very limited. When the network topology determines a higher alignment between local and global aims, such as in the case of the dependent pattern (Capaldo and Giannoccaro, 2015a), trust is not useful to improve the adaptive capacity of the system, so that resilience is undermined. Conversely, trust is beneficial at most when the network topology creates high risks of conflicting aims, resulting from the dis-alignment between the local optima of the single firms and the global optimum of the entire system. Trust, enabling integration, resolves this problem, so that the ability of the system to find better configurations is improved.

Finally, we also computed the recovery time, i.e. the time required by the supply network to restore the supply network performance obtained in a static environment (i.e. with no disruption). To this aim, we simulated the supply network performance for all topologies in the static scenario and computed the average number of steps needed to reach the average performance achieved in the static environment (Table 3). We note that the recovery time on average is lower when trust is absent or low than when trust is high. This can be explained by the fact that the supply network performance in static environments is higher when trust is high than when trust is low or absent, so that the system takes more time to restore the static performance. In other words, a supply network with high trust is slower to return to the performance achieved before the disruption occurred, than a supply network with low or no level of trust, only because a higher performance value should be restored. The only exception to this finding is in the case of the dependent pattern. In such a case, the recovery time for a high trust level is lower than in the case of low/no trust. This can be explained by looking at the supply network performance in the static environment: when trust is low or absent, the performance is higher than in the case of high trust. Therefore, in such a case the supply network takes more time to restore the performance than when trust is high.

Table 3. Recovery time and supply network performance in static environments.*

Topology	Recovery time			Performance in static environment		
	High Trust	Low Trust	No Trust	High Trust	Low Trust	No Trust
Block diagonal	20.00	18.25	17.50	0.8897	0.8787	0.8551
	(2.94)	(2.75)	(1.29)	(0.057)	(0.060)	(0.059)
Centralized	28.50	22.50	25.30	0.9151	0.8994	0.8873
	(3.79)	(1.92)	(1.16)	(0.057)	(0.058)	(0.063)
Dependent	8.75	9.50	11.25	0.8424	0.8427	0.8481
	(1.89)	(1.00)	(1.71)	(0.045)	(0.047)	(0.049)
Diagonal	27.75	22.50	15.50	0.8937	0.8927	0.8626
	(2.22)	(1.92)	(2.65)	(0.058)	(0.058)	(0.058)
Hierarchical	20.00	22.70	21.00	0.8950	0.8952	0.8812
	(1.41)	(2.08)	(0.82)	(0.054)	(0.057)	(0.059)
Local	29.00	21.50	17.75	0.8977	0.8810	0.8429
	(2.71)	(1.29)	(2.50)	(0.065)	(0.063)	(0.060)
Preferential Attachment	24.75	22.75	18.25	0.8970	0.8872	0.8602
	(3.59)	(5.25)	(2.63)	(0.061)	(0.063)	(0.058)
Random	31.30	26.50	27.30	0.8960	0.8814	0.8584
	(4.04)	(7.33)	(2.31)	(0.066)	(0.065)	(0.065)
Scale-free	26.00	25.00	20.75	0.9007	0.8927	0.8695
	(3.37)	(3.46)	(3.69)	(0.061)	(0.062)	(0.064)
Small-world	28.50	25.50	19.75	0.8965	0.8837	0.8517
	(2.65)	(1.73)	(1.26)	(0.067)	(0.063)	(0.062)

*Standard deviation given in parentheses

6. THEORETICAL AND MANAGERIAL IMPLICATIONS

From the theoretical point of view, this study contributes to the literature on the drivers of the resilience of the supply networks, by examining the role of network-level trust. Our findings confirm that trust is an antecedent of supply network resilience (Soni et al., 2014; Dubey et al., 2018), showing that higher levels of trust are associated with higher supply network performance in all the examined topologies. However, while previous studies have explained the positive effect of trust on supply network resilience thanks to information sharing and collaboration among partners, we theorized and demonstrated that trust across partnering firms enhances the ability of the supply networks to adapt to disruptions, which in turn improves its resilience. Thus, we add to the current knowledge that network-level trust is a valid strategy to enhance the resilience of the supply network according to a dynamic perspective, an issue not investigated so far. We clearly showed that trust permits the system to identify desirable configurations better than those that could be selected when trust is low or absent, especially when there is a high risk of conflicting aims among supply network firms. However, we also showed that due to this higher adaptive performance, the time needed to restore the supply network performance is higher in the supply networks characterized by high levels of trust.

Furthermore, our study provides an additional contribution by highlighting in which contexts trust is a valid strategy to enhance dynamic resilience. Since the frequency of the event is a critical variable to classify disruptions (Dolgui et al., 2018), we analyzed its moderating effect on the relationship between trust and resilience. Our findings suggest that the higher the frequency of disruptions, the lower the beneficial effect of trust for supply network resilience. This means that trust is a proper strategy to build a resilient supply network able to cope with the ripple effect, especially when disruptions occur at a low rate.

Furthermore, our study extends previous research on structural drivers of supply network resilience, which have mainly examined the direct effect of network topology, density, complexity, node criticality on resilience (Craighead et al., 2007; Falasca et al., 2008; Blackhurst et al., 2011; Brandon-Jones et al., 2014; Ivanov et al., 2014; Kim et al., 2015; Li et al., 2017). We investigated the interaction effect of trust with the network topology on supply network resilience. In doing so, we extend previous research by Kim et al. (2015), who showed the existence of a direct effect between the supply network topology and resilience in the case of a firm removal. Compared to this study, we included more topologies in our analysis and also considered the interaction effect played by network topology in the relationship between trust and resilience. We identified for which topologies trust is the most suitable strategy to improve resilience. In particular, our findings demonstrate that resilience performance associated with trust significantly vary across the ten topologies analyzed. This represents a novel contribution to the literature.

Particularly, the dependent pattern reveals the lowest beneficial effect of trust on resilience performance compared to other supply chain patterns. Similarly to dependent structure, other structures where trust is scantly beneficial for resilience are hierarchical, diagonal and centralized. Our results show that the local pattern is associated with the highest beneficial effect of trust on resilience performance. Since supply networks adopting just in time strategy may show a local topology, we suggest them to rely on trust as a critical success factor to enable resilience. Small world, random and block-diagonal patterns also are associated with high resilience enhanced by trust, while the scale-free and preferential attachment patterns demonstrate a moderate beneficial impact of trust on resilience performance.

Our study also makes a contribution to the literature from a methodological point of view. It proposes a model to study supply network resilience based on the NK simulation. As noted by Dolgui et al. (2018), the most preferred simulation approaches applied to study the resilience of supply networks are system dynamics, agent-based modelling, and discrete-event simulation. Our approach belongs to agent-based simulation and employs the NK fitness landscape (Kauffman, 1993). This methodology provides several benefits compared to other simulation tools, as it permits to capture the complex nature of supply networks as well as to model the adaptive capacity of the system (Giannoccaro, 2011; Capaldo and Giannoccaro, 2015a,b; Giannoccaro et al., 2018) in an easy and controlled manner. Furthermore, since it permits to compute and compare the performance of supply networks adopting multiple network topologies, it provides further support to the consideration that a simulation is a suitable approach for analysing disruptions and resilience in supply networks (Ivanov et al., 2017; Hosseini et al., 2019).

Moreover, this approach offers the possibility to study supply chain disruptions from a network level perspective. This extends previous studies that have used network theory (Kim et al., 2015; Ivanov, 2017). This allows us to answer a recent call concerning the use of network-based and complex system methodologies to investigate, in general, the resilience of complex systems (Fraccascia et al., 2018) and, specifically, resilience of supply networks (Hosseini et al., 2019; Dolgui et al., 2018).

Our findings provide interesting implications for practice. They suggest that to improve the resilience of supply networks, managers should develop network-level trust. This implies that different trust-developing tools and mechanisms should be promoted, for example by resorting to long term contracts, by adopting profit and risk sharing mechanisms, by devoting time and resources to increase visibility, information sharing, and collaboration across the partnering firms, by punishing opportunistic behaviours, and by rewarding goodwill and collaboration when disruptions occur. Therefore, since nurturing trust in supply networks is time-consuming, expensive, and requires efforts, we argue that the advisability for developing trust, to improve resilience, varies depending on the specific supply network topology. Consequently, we first advise managers interested to enhance resilience to pay careful attention to the network topology of their supply network, which should be clearly assessed. This calls for an extensive supply network mapping, usually neglected in practice, because of time and effort required, as recently advocated by Choi et al. (2020). Then, trust development efforts must only be directed to those topologies where high beneficial impacts on resilience are expected at a higher extent. Based on our findings, since local topologies are expected to be exhibited by supply networks implementing just in time strategy, it is highly recommended in such a case to rely on trust for improving the resilience. Similarly, for supply networks producing modular products (i.e. having block diagonal topology) and in the case of the hub and spoke networks (i.e., scale-free topology), nurturing trust is advised as the proper way to increase resilience. Conversely, as shown by our findings, in the case of a dependent topology, which may be exhibited by supply networks adopting postponement strategy, we caution to resort on trust as a mechanism to enhance resilience.

7. CONCLUSIONS

Enhancing the resilience of supply networks is fundamental to deal with the ripple effect. This paper analyzed the role of trust as an antecedent of the supply network resilience in different contexts, by conceptualizing it as the ability of the system to adapt to disruptions occurring in the environment. In particular, we examined the effect of trust on the resilience of supply networks exhibiting ten different network topologies, i.e. random, local, small-world, block-diagonal, preferential attachment, scale-free, hierarchical, diagonal, centralized, and dependent. This is in line with recent recommendations of the literature that advises relying on complex network theory to investigate the structural antecedents of supply network resilience. Our main finding was that the extent to which trust is beneficial for supply network resilience considerably varies across the network topologies, an issue scantly investigated so far.

Our findings provided interesting implications both for theory and practice. In particular, since developing trust may be an expensive task, involving time and resources, we caution managers to develop trust only for those supply network topologies for which the expected benefits in terms of resilience are high.

Our work has some limitations, which could be addressed in future research. First, our model does not explicitly include the cost of developing trust but only simulate the benefits in terms of enhanced adaptive performance. A future improvement of the model will consist of explicitly introducing this cost in the analysis. Further research will be also devoted to empirically testing the main findings achieved in real supply networks. In particular, we are interested to investigate the beneficial effect of trust in supply networks adopting just in time strategy, an issue that merits further investigation.

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Appendix A

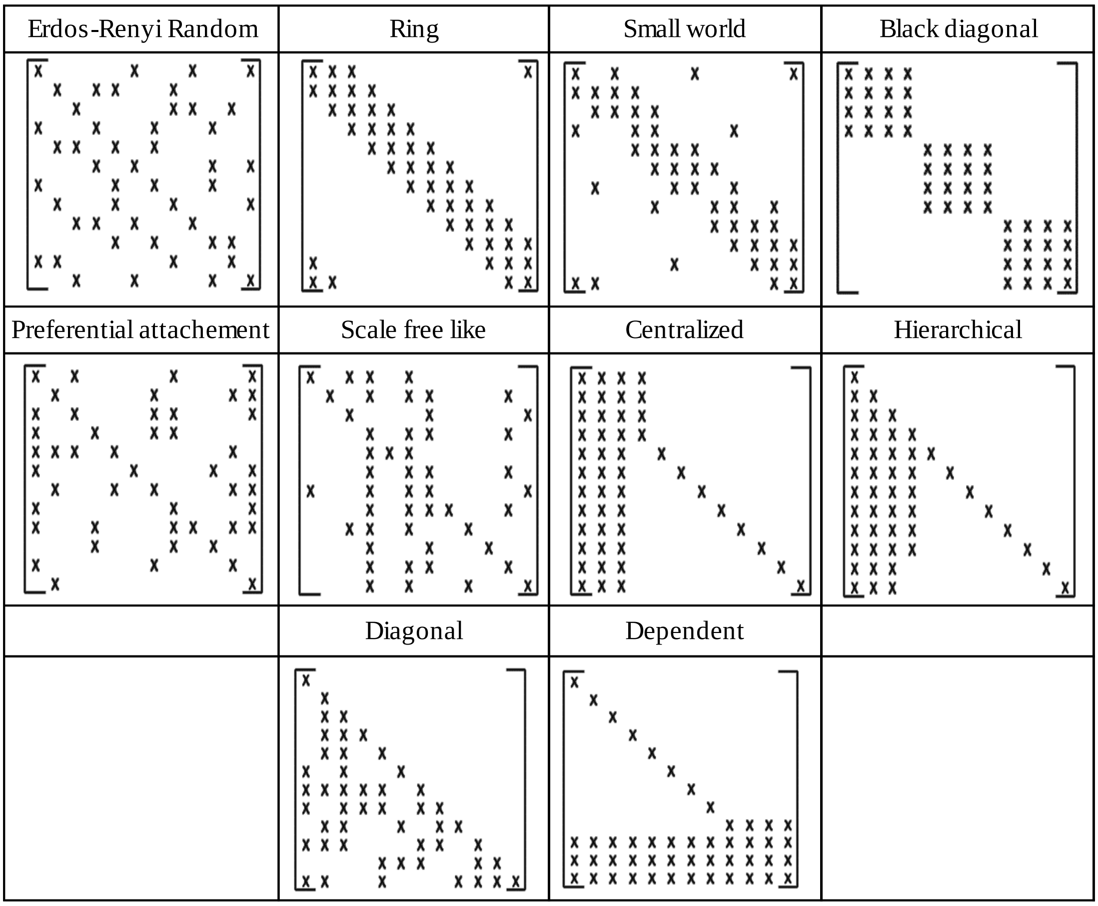

Figure 1A. The influence matrices of the ten supply network topologies.

Appendix B.

Table B1. Standard deviations of resilience performance

	Trust				Trust		
	High	**Low**	**No**		**High**	**Low**	**No**
BLOCK-DIAGONAL				**LOCAL**			
Δ=40	0.0639	0.0645	0.0628	Δ=40	0.0650	0.0671	0.0652
Δ=20	0.0594	0.0609	0.0601	Δ=20	0.0608	0.0628	0.0612
Δ=10	0.0514	0.0538	0.0528	Δ=10	0.0499	0.0540	0.0537
CENTRALIZED				**DEPENDENT**			
Δ=40	0.0676	0.0660	0.0623	Δ=40	0.0840	0.0840	0.0823
Δ=20	0.0607	0.0579	0.0567	Δ=20	0.0712	0.0705	0.0694
Δ=10	0.0511	0.0500	0.0478	Δ=10	0.0568	0.0553	0.0551
DIAGONAL				**HIERARCHICAL**			
Δ=40	0.0614	0.0579	0.0579	Δ=40	0.0606	0.0602	0.0632
Δ=20	0.0535	0.0555	0.0532	Δ=20	0.0582	0.0530	0.0530
Δ=10	0.0486	0.0448	0.0455	Δ=10	0.0488	0.0480	0.0450
RANDOM				**SMALL WORLD**			
Δ=40	0.0692	0.0729	0.0716	Δ=40	0.0667	0.0676	0.0685
Δ=20	0.1036	0.1003	0.0992	Δ=20	0.0619	0.0639	0.0623
Δ=10	0.0537	0.0558	0.0556	Δ=10	0.0513	0.0532	0.0545
SCALE-FREE				**PREFERENTIAL ATTACHMENT**			
Δ=40	0.0639	0.0620	0.0582	Δ=40	0.0629	0.0612	0.0614
Δ=20	0.0570	0.0587	0.0566	Δ=20	0.0572	0.0580	0.0555
Δ=10	0.0508	0.0502	0.0487	Δ=10	0.0505	0.0513	0.0496