The Impact of Control and Complexity on Supply Network Performance: An Empirically Informed Investigation Using NK Simulation Analysis

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ABSTRACT
Control over suppliers is a core issue for a buying firm. Despite the amount of research on the topic, how much of its supply network (i.e., scope of control) a buying firm should control, so as to increase supply network performance, is a question that has not received adequate research attention. The study addresses this research question by considering the supply network as a complex adaptive system and developing an empirically informed agent-based simulation model using the NK fitness landscape framework, to examine how varying levels of scope of control influence supply network performance. We also investigate the direct effect of two supply network complexity dimensions (i.e., number of firms and level of supply interactions) on supply network performance and the moderating effect played by the scope of control. Results show that the relationship between scope of control and supply network performance follows an inverted-U shape. Furthermore, we find that the complexity dimensions negatively affect supply network performance with the performance decrease depending on the scope of control. Based on these findings, we formulate different control strategies to mitigate the negative influence of complexity. [Submitted: December 3, 2015. Revised: August 16, 2017. Accepted: August 21, 2017.]

Subject Areas: Complexity, Control, Network Performance, and NK Simulation Supply Network.

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INTRODUCTION

Control is the coordination process that regulates behaviors of organizational members toward the achievement of the organizational goals (Bradach & Eccles, 1989; Cardinal, Sitkin, & Long, 2004). Control in interconnected organizational context, such as a supply network (SN), refers to the process by which partnering firms influence the members of the system to behave in a manner that achieves system-level objectives (Inkpen & Currall, 2004; Tiwana & Keil, 2010). Studies on control show that SN performance improvements, in terms of cost reduction, delivery, quality, and shorter cycle time, can be achieved by means of planning, implementation, measurement, and control of SNs (cf. Mabert & Venkataramanan, 1998). For example, powerful buyers induce working relationships among suppliers (Choi & Hong, 2002), mandate suppliers to adopt specific production technologies and information and communication technologies (Iskandar, Kurokawa, & LeBlanc, 2001), incorporate managerial practices such as TQM and JIT (MacDuffie & Helper, 1997; Kelle, Al-khateeb, & Miller, 2003) as well as collaborative operational techniques such as the CPFR or VMI (Mishra & Raghunathan, 2004; Kouvelis, Chambers, & Wang, 2006; Aviv, 2007) and expect just-in-sequence (JIS) production and delivery of modules from suppliers (Wagner & Silveira-Camargos, 2012).

Research has analyzed different modes of control, mainly distinguishing between formal and informal control (Li et al., 2010; Tiwana & Keil, 2010; Liu, 2015). While formal control of behavior and outcome is accomplished by means of contracts (Li et al., 2010; Liu, Wang, & Huang, 2017), informal control uses clan and self-control mechanisms (Liu, 2015). In these studies, control is viewed as a dyadic and unidirectional construct exerted by the controller (usually the buyer) on the controlee (usually the supplier) (Stouthuysen, Slabbinck, & Roodhooft, 2012). These studies have not considered the complex adaptive nature of SNs. Self-organization and adaptation are key properties in these networks that compose of several firms that are interconnected with each other (Nooteeboom, 1999; Choi, Dooley, & Rungtusanatham, 2001; Lang, Deflorin, Dietl, & Lucas, 2014). No singular authority or mechanism deliberately orchestrates the overall system behavior. Therefore, the outcome is a spontaneous result of the local interactions among interdependent agents purposefully pursuing their individual goals, based on their local information, and continuously adapting to feedback received from others (Chiles, Meyer, & Hench, 2004). For these reasons in complex adaptive networks, control can influence performance outcome in a way different to what the literature on the management of buyer–supplier relationships predicts.

In this study, we focus on the scope of control, an issue that to the best of our knowledge has not yet received adequate attention in the literature. We define the scope of control as the number of suppliers in the entire SN that the focal company controls either by itself or with the help of the first-tier supplier. Depending on the scope of control, the ability of the SN to adapt could vary, resulting in different SN performance. On the one hand, the focal firm may desire to control the entire SN so as to improve the system-level performance (Lee & Billington, 1992; Chen, 2003), but such an approach could result in slowing the decision-making process (Carzo & Yanousas, 1969), reducing heterogeneity and limiting the efficacy of adaptation (Jones, 2000). It follows that, from the perspective of the focal firm that has the
ability to exert control on various members of an SN, it is strategically important to consider how much of the network should be controlled so as to increase SN performance. For instance, in the case of the center console, Honda and Chrysler have chosen different approaches on how they control their respective SNs (cf. Choi & Hong, 2002). Honda tends to engage in more of a formal centralized control of its lower tier suppliers; for instance, Honda establishes a contractual agreement directly with leather parts and fastener suppliers at the third tier by which it assures the control of product cost and quality. In contrast, Chrysler does not have contractual agreement with third-tier suppliers. It delegates more of its design work to its first-tier suppliers. The decisions by the focal firm as to how much to control inevitably affects the overall SN performance. To understand this effect better, our study focuses on the following key research question: What is the relationship between the scope of control and SN performance?

The study also investigates how SN complexity influences SN performance. Complexity in SN refers to multiple dimensions (Choi & Hong, 2002; Bozarth et al., 2009; Bode & Wagner, 2015; Brandon-Jones, Squire, & Van Rossenberg, 2015), but in line with the complex adaptive nature of SN and in concert with previous studies on the topic, we focus on the level of supply interactions and the number of firms (Choi & Hong, 2002). SN complexity has been shown to adversely influence performance such as cost, quality, delivery time, and frequency of disruptions (Craighead et al., 2007; Bozarth, Warsing, Flynn, & Flynn, 2009; Larsen, Manning, & Pedersen, 2013; Bode & Wagner 2015; Brandon-Jones et al., 2015; Mizgier, Wagner, & Jüttner, 2015). The findings of these studies show that as complexity increases, buyers and suppliers find it more difficult to coordinate their SN and hence the SN performance, characterized in terms of the ability of the network to satisfy customer requirements, suffers. We reason that this performance decrease is a function of the adaptive behavior set in motion due to complexity-related factors in an SN. The extant literature lacks clarity regarding how SN complexity affects adaptive outcome. By means of this study, we intend to address this gap.

To pursue our research aims, we use a simulation-based approach to model SN (Nair, Narasimhan, & Choi, 2009) and develop an NK simulation model that is based on empirical data that we collected from Honda. In particular, the network data of the Accord’s center console are used to calibrate the NK model parameters and build the baseline model using real values concerning the critical variables of this study (i.e., the number of firms, number of supply interactions among firms, relative power of the focal company vis-à-vis suppliers in the network, and level of formal control exerted on upstream suppliers). Our interactions with Honda managers during the empirical data collection revealed that Honda exerts control on its supply base with the help of its first-tier suppliers. Hence, in this study, we conceptualize the notion of scope of control to include formal control exerted by either the focal firm (i.e., Honda) or its first-tier suppliers. Complexity is associated with the number of firms and the level of interconnections in the SN.

We adopt Kauffman’s NK model (1993) for this study because it has been recognized as a powerful research methodology for theory building and theory testing in operations management, organizational behavior, and strategy (Rivkin, 2001; Lenox, Rockart, & Lewin, 2006; Davis, Eisenhardt, & Bingham, 2007; Ganco & Hoetker, 2009; Kavadias & Sommer, 2009; Mihm, Loch, Wilkinson, &
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Huberman, 2010; Aggarwal, Siggelkow, & Singh, 2011; Siggelkow, 2011; Lang et al., 2014). This methodology fits very well with our research aims and it enables us to overcome the limitations of previous studies on control in SNs, which mainly focus on buyer–supplier relationships using analytic and qualitative approaches. First, the NK model helps in capturing the complex adaptive nature of SNs (Choi et al., 2001; Choi & Krause, 2006; Pathak, Day, Nair, Sawaya, & Kristal, 2007; Lang et al., 2014; Capaldo & Giannoccaro, 2015a, 2015b), which, as previously discussed, is required to properly study the relationship between control and SN performance. Second, this method is suitable to capture emergence and adaptation in SNs (Giannoccaro, 2011; Capaldo & Giannoccaro, 2015a, 2015b). It is also appropriate to model organizational variables such as control and show how they affect the adaptation process of the system (Rivkin & Siggelkow, 2003; Siggelkow & Levithal, 2003; Siggelkow & Rivkin, 2005; Aggarwal et al., 2011). Third, compared to other simulation models (such as systems dynamics and agent-based modeling), it is well suited to model the system complexity arising from the number of elements ($N$) and the interactions among them ($K$) in a controlled manner. Specifically, it provides a rigorous approach to investigate the effect of both complexity dimensions on the adaptive performance of a system (Davis et al., 2007). Finally, as compared to analytical, econometric, psychometric, and qualitative research, the NK model permits an extensive investigation of the relationship between the variables by considering multiple experimental scenarios. The possibility to fine-tune the complexity parameters as well as the scope of control exerted by the focal company allows us to run multiple experiments and compare their results in a way that will be difficult with other methods.

The results of this study present interesting new findings. The scope of control is nonlinearly related to the SN performance. As the scope of control increases, SN performance initially increases but then decreases. Results concerning complexity are also intriguing. Both dimensions of complexity (number of firms and number of interrelationships among firms) are negatively related to SN performance, but the extent of performance decrease depends on the scope of control exerted by the focal company in the SN.

The rest of the article is organized as follows. In the next section, we present theory concerning how SN performance is influenced by the scope of formal control and the degree of complexity in the SN. Then, we describe the computational model and explain how the main variables of the conceptual model have been operationalized. In the fourth section, we provide details concerning the empirical data used to build the baseline simulation model and information regarding the additional experiments we run to investigate the conceptual model. Next, we present the simulation results and the validation issue. The article concludes with a discussion of the key insights and suggestions for future research directions.

**THEORY**

**The Issue of Control in Supply Networks**

The past two decades have seen an increasing attention devoted to the proactive management of SNs (cf. Mabert & Venkataramanan, 1998). The vision has been
that the end-to-end SN from raw material suppliers to end customers can be
designed and managed by a unique decision maker (i.e., the focal firm), who plans
and makes decisions for the whole system so as to optimize the global performance
(Tsay, Nahmias, & Agrawal, 1999). The common thesis in this stream of research
is that supply chain control is a key source of competitive advantage (Lee &
Billington, 1992; Lee, Billington, & Carter, 1993; Huang & Iravani, 2005; Tiwana
& Keil, 2010; Stouthuysen et al., 2012). Control leads to cost reduction, improved
delivery, and shorter cycle time (Carr & Ng, 1995; Narasimhan & Jayaram, 1998;
Chen, 2003). In essence, formal control can help a focal firm to orchestrate the SN
in a way that it addresses customer requirements.

Ultimately, these benefits come from managing all the interdependencies
existing inside an SN and by providing a way to overcome conflicting goals
among the firms in the SN (Lee, Padmanabhan, & Whang, 1997; Tsay et al.,
1999). If an SN is managed by local independent efforts, the interdependencies
are neglected and this could lead to inefficiency of the whole system, even though
each firm might be optimizing their performance (Christopher, 1992; Watts &
Hahn, 1993; Watts et al., 1995; Simchi-Levi et al., 2000; Vickery et al., 2003).
For example, the use of independent forecasting techniques and the adoption of
unsynchronized order batching policies by firms in an SN cause one of the most
harmful phenomena for the efficiency of an SN known as the bullwhip effect
that manifests in the amplification of demand variability (Lee et al., 1997, 2004).
A number of successful SN control practices have been implemented across a
variety of industries by formal contractual means. These include quick response
(QR) method, vendor-managed inventory (VMI), comanaged inventory (CMI),
and jointly managed inventory (JMI) (see Simchi-Levi et al., 2000, for a review).

Although it would be desirable for the entire SN to be managed by a single
entity so that the system performance can be improved (Lee & Billington, 1992;
Chen, 2003), a dissenting perspective suggests that complete control of the entire
system performed by a single entity can result in producing tall hierarchies that
are slow to process decisions (Carzo & Yanousas, 1969) and can invariably reduce
heterogeneity (Morgan, 1997; Jones, 2000). By limiting autonomy, an OEM can
inhibit suppliers from exploring new ways of completing their tasks. Langfred
and Moye (2004) emphasize the advantage accorded by autonomy in terms of in-
formational mechanisms by noting task-related informational asymmetry between
the supervisor and subordinate. Similar informational asymmetry exists in SN. In
such situations, control reduces the discretion to implement these tasks efficiently
(Langfred & Moye, 2004). With autonomy, suppliers are able to make necessary
changes and modifications, thereby improving SN performance.

This implies that from a focal firm’s perspective, some scope of control is
good but too much can hurt performance. Thus, the focal firm needs to make a
conscious choice of how much of the SN should be controlled. The scope of control
could theoretically range from very low (e.g., a case of no firm being controlled
by the focal company) to very high (e.g., a case of all firms being controlled by
the focal company). Some control improves network-level coordination and helps
in aligning the conflicting goals of supply chain partners, thereby improving SN
performance. With no control, coordinated activities become difficult, conflicting
goals persist, and SN performance suffers. At the same time, as the scope of control
keeps increasing beyond a threshold (i.e., more than a certain number of suppliers in the SN being controlled by either the focal firm or its first tier supplier), SN performance can deteriorate because it limits the autonomy of several suppliers, thereby constraining their ability to adapt. Based on these arguments, we present the following hypothesis:

**H1.** As the scope of control increases, the performance of the SN first increases and then decreases.

The Complexity of Supply Networks

Complexity is a critical characteristic of SNs. Studies on the topic have highlighted its multidimensional nature and focused on different sources of complexity (Jacobs & Swink, 2011; Manuj & Sahin, 2011). Complexity has been shown to associate with three main features of a system: the multiplicity, the diversity, and interrelatedness (Jacobs & Swink, 2011). Multiplicity and diversity, often referred to as structural complexity, concern the complexity associated with number and variety of elements defining the system. Interrelatedness, also called operational complexity, refers to the interactions between the elements of the system.

In an SN, the structural complexity dimension includes vertical complexity (i.e., the number of firms in the SN and the number of tiers in the SN) (Mentzer et al., 2001; Choi & Hong, 2002), horizontal complexity (i.e., the number of suppliers in each tier) (Choi & Hong, 2002; Bode & Wagner, 2015), and spatial complexity (i.e., the geographical dispersion of the SN) (Choi & Hong, 2002; Bode & Wagner, 2015). Structural dimensions are considered to increase SN complexity, because of the greater number of information, data, and heterogeneity (culture, language, etc.) that should be taken into account to effectively and efficiently manage the SN (Choi & Hong, 2002). The SN operational complexity mainly concerns the level of supplier interactions or, equivalently, interrelationships (Vachon & Klassen 2002; Choi & Krause, 2006; Bozarth et al., 2009). It causes lower SN performance because it increases the interdependence among partnering firms, which, in turn, results in higher need for coordination, conflicting aims, and trade-offs that are not easily resolved. In concert with this stream of research, we consider the number of firms in the SN to represent the structural complexity and the interrelationship between firms in the SN to represent operational complexity.

Studies have emphasized that complexity dimensions adversely influence SN performance (Bozarth et al., 2009; Larsen et al., 2013). In particular, complexity has negative implications on overall plant performance (Bozarth et al., 2009), frequency of disruptions (Craighead et al., 2007; Bode & Wagner, 2015), responsiveness (Choi & Krause 2006), and delivery speed (Vachon & Klassen, 2002). Brandon-Jones et al. (2015) show that the vertical, horizontal, and spatial complexity differently impact disruptions. Specifically, their results show that the number of firms and the uncertainty of lead times influence the frequency of disruptions but that geographic dispersion and the differentiation of suppliers do not have significant effects on this frequency. Bozarth et al. (2009) find that the dynamic (operational) complexity has a negative stronger impact on plant performance than detailed (structural) complexity. Building on this literature, we hypothesize:
**H2a.** More supply interactions among firms in an SN is negatively associated with SN performance.

**H2b.** Higher number of firms in an SN is negatively associated with SN performance.

As SN complexity due to the level of supply interactions among firms rises, SN performance diminishes because of the need to coordinate activities and resolve a high number of conflicting objectives among partnering firms. In such a case, we reason that a high scope of control is beneficial because the focal firm can act as a coordinating agent to manage the interdependencies among activities and trade-offs emanating from conflicting objectives. By having control on a higher number of suppliers that are highly interconnected with each other, the focal firm is able to provide and access information in such a way so as to exercise control as well as tap diverse knowledge bases (Dyer and Nobeoka, 2000). Thus, the decrease in SN performance is ameliorated by means of higher scope of formal control. Accordingly, we hypothesize:

**H3a.** Higher scope of formal control helps in reducing the negative effect of complexity emanating from the level of supply interactions among suppliers on SN performance.

Exerting formal control when the SN is characterized by a large number of firms is difficult (Flamholtz, Das, & Tsui, 1985; Snell, 1992). Controlling the multitude of firms requires high level of decision-making capability because as the number of firms grows, more information and data needs to be taken into account (Choi & Hong, 2002). In such a case, we reason that high scope of control will be detrimental for SN performance, because it creates a situation of information overload on the focal firm. Frequent information sharing with a large number of suppliers can create challenges for the focal firm and can adversely impact SN performance. Accordingly, we hypothesize:

**H3b.** Higher scope of formal control intensifies the negative effect of complexity emanating from the number of suppliers on SN performance.

Figure 1 shows the conceptual model under investigation.
MODEL DEVELOPMENT

Building the NK Model of the SN

The NK model advanced by Kauffman (1993) in the context of evolutionary biology consists of a tunable family of fitness landscapes. In particular, it provides a stochastic procedure to design fitness landscapes with controlled complexity, which has recently become popular for modeling decision problems in organizational settings (Levinthal, 1997; Gavetti & Levinthal, 2000; Rivkin, 2001; Siggelkow & Rivkin, 2005; Aggarwal et al., 2011; Siggelkow, 2011).

In a generic NK model applied to the single firm, the firm is modeled as a vector of \(N\) binary decisions. These binary decisions can be viewed as abstract representations of firm-level decisions such as developing the marketing plan, developing the production plan, developing new products, etc. \(N\) reflects the number of decisions in the SN and \(K\) is the number of interactions among them. A matrix (called influence matrix) records which decisions interact with each other. \(N\) and \(K\) control the complexity of the decision-making problem that the focal firm should resolve.

A specific \(N\) digit vector \(d = (d_1, d_2, ..., d_N)\) identifies the configuration of the system (state), i.e., the specific set of choices on the decisions made by the firm. Each configuration is associated with a fitness value (payoff – \(P(d)\)), which stands for any firm performance. The map obtained from all the possible choice configurations (\(2^N\)) on attendant payoffs is called the fitness landscape. The firm is supposed to be engaged in a decision-making problem to discover the best choice configuration, i.e., the one with the highest payoff. This process is also conceived as an adaptive “walk” through a landscape, made up of valleys and peaks. According to the landscape metaphor, in fact, each configuration corresponds to a point and payoff represents the height. Thus, the aim is to discover and occupy the highest peak (global peak) of the landscape.

The efficacy of the adaptive walk to find the global peak is affected by the ruggedness of the landscape. The latter is controlled by the parameter \(K\)—for higher values of \(K\), the landscape is more rugged and the adaptive walk is less effective (Kauffman, 1993). This occurs because as \(K\) rises, the number of local peaks proliferates, thereby increasing the chance that the adaptive walk remains trapped into a suboptimal location. The efficacy of the adaptation also depends on the searching algorithm, which has been employed to model organizational features such as the level of centralization (Rivkin & Siggelkow, 2003; Siggelkow & Levinthal, 2003) and the level of modularization (Ethiraj & Levinthal, 2004). The adaptive performance of the SN is measured by the number of replications in which the highest peak is found and by the payoff of the configuration at the end of the adaptive walk measured as a percentage of the highest peak and averaged across replications (Ganco & Hoetker, 2009).

In concert with recent applications of the NK model to the SNs (Giannoccaro, 2011, 2015; Capaldo & Giannoccaro, 2015a, 2015b), the SN is framed as a vector of \(N\) interacting decisions made by the SN firms \((d_1, d_2, ..., d_N)\) and each configuration of choices on decisions is associated with a payoff value, which represents the overall SN performance. As mentioned earlier, the decisions made by the firms in the SN can be abstracted as various operational activities, such as
inventory replenishment, demand forecasting, production planning, transportation schedule, and so on.

In our model, for the sake of simplicity and without any loss of generality, we assume that each firm makes a single decision (e.g., how much to stock). Thus, the number of decisions $N$ corresponds to the number of firms in the SN. In an SN, decisions made by firms interact with each other and the level of interaction is captured by the parameter $K$. Interactions occur because firms are interdependent to address customer requirements (Capaldo & Giannoccaro, 2015b). In particular, the existence of a buyer–supplier relationship makes the impact of the buyer’s decision on the SN payoff contingent on the supplier’s decision. For example, if the buyer decides to stock a high quantity of a given product but the supplier simultaneously decides to stock a low quantity for the respective component, because of the consequent shortage of the product the total profit for the SN will be lower as compared to the case when the quantity decisions of the supplier and buyer are synchronized. Therefore, the impact of the decision of the buyer concerning the quantity to stock on total SN performance is influenced by how much the supplier decides to stock. Any material flow link from a supplier to the buyer corresponds to an interaction between the decision of the buyer and that of the supplier. The influence matrix thus corresponds to the material flow network.

**Generation of the Fitness Landscape**

Once $N$, $K$, and the influence matrix of the model are defined, the fitness landscape corresponding to the SN can be generated. Thus, the landscape is defined by these three parameters. Specifically, the landscape is the map that associates each configuration of choices on decisions ($d$) with the attendant SN performance ($P(d)$). To generate the landscape, we follow the classical NK procedure (Kauffman, 1993), where each configuration is assigned with a payoff value that is computed by averaging the contribution of each decision $C_i$ to the total payoff. The contribution, $C_i$, of each decision $d_i$ is generated by drawing at random from a uniform $U[0,1]$ distribution. However, because of interactions among decisions, $C_i$ depends not only on the choice of the decision $i$ (0 or 1), but also on the choice of the interacting decisions $K$. Therefore, in the case of $K = 0$, $C_i$ assumes only two values, which means that all the choice configurations (i.e., each possible combination of decisions) with $d_i = 0$ would have the same $C_i$, and all the choice configurations with $d_i = 1$ would share different $C_i$. When $K = N-1$, the contribution of each decision depends on how all the other decisions are resolved; thus, $C_i$ differs in any choice configuration. See the Appendix for more details.

Given a choice configuration $d$, each $C_i$ represents the contribution of the firm $i$ to the SN performance in that configuration. The SN payoff assigned to each choice configuration is given by $\Sigma_i C_i / N$. Taking the average of single contributions means that all firms equally contribute to SN payoff. The fitness landscape so generated gives all the possible performance the SN can achieve and captures how they are affected by the complexity of the SN, i.e., $N$ and $K$.

**Adaptive Process**

The adaptive walk on the fitness landscape follows a specific searching strategy determined by (i) the number of searching agents and (ii) the searching procedure.
Table 1: Coding exemplar levels of control.

<table>
<thead>
<tr>
<th></th>
<th>33% Scope of Control</th>
<th>55% Scope of Control</th>
<th>100% Scope of Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>(v_{FC})</td>
<td>((d_1, d_2))</td>
<td>((d_1, d_2, d_5, d_6))</td>
<td>((d_1, d_2, d_5, d_6, d_7, d_8, d_9, d_{10}))</td>
</tr>
<tr>
<td>(v_{1stS})</td>
<td>((d_3, d_4))</td>
<td>((d_3, d_4))</td>
<td>((d_3, d_4))</td>
</tr>
<tr>
<td>No. of vectors of autonomous firms</td>
<td>6</td>
<td>4</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: % scope of control = (Number of suppliers controlled by the focal firm + number of suppliers controlled by the first-tier supplier)/(Network size -1); Network size = 10.

Similar to other studies applying these variables to code different coordination modes (Rivkin & Siggelkow, 2003; Siggelkow & Rivkin, 2005; Giannoccaro, 2011), we used them to model the scope of control in the SN. Hence, the adaptive performance is strictly dependent on the scope of control exerted by the focal firm in conjunction with the first-tier supplier within the SN. Thus, it is important to note that changing the scope of control does not modify the landscape but only the search algorithm used.

**Searching Agent**

We define three types of searching agents: the focal firm, the first-tier supplier, and autonomous upstream supplier. Prescribing the scope of formal control determines which suppliers are controlled by the focal firm, which ones are formally controlled by the first-tier supplier, and which suppliers are autonomous. This is modeled by splitting the vector of decisions made in the entire SN, \(v_{SN} = (d_1, d_2, \ldots d_N)\), into a number of subvectors with a specific dimension (i.e., the number of decisions) managed by each searching agent. Subvectors consist of: (i) the vector of decisions controlled by the focal firm \(v_{FC}\), (ii) the vector of decisions controlled by the first-tier supplier \(v_{1stS}\), and (iii) the vector of decisions made by the autonomous firms. Table 1 shows the code for the scope of formal control by the focal firm and first-tier supplier in exemplar scenarios considered in our experiments.

As the focal firm increases (decreases) the use of the first-tier supplier to control upstream suppliers, the dimension of \(v_{1stS}\) becomes higher (lower) and the dimension of \(v_{FC}\) becomes lower (higher). As the scope of formal control decreases, the number of autonomously searching agents increases.

**Searching Procedure**

When agents (focal firm, first-tier supplier, and autonomous suppliers at lower tiers) are engaged in a searching process, they look for new configurations to adopt to improve payoff. The adaptive walk entails an iterative process. The focal firm proposes a new alternative configuration \(v_{FC}\). If the new configuration of \(v_{FC}\) improves its total payoff function, the focal firm adopts it; otherwise, the previous configuration is maintained. The same holds for the first-tier supplier. A proposed configuration \(v_{1stS}\) is adopted only if it improves its total payoff \(P_i\).

However, to correctly investigate the effect of the scope of control on SN performance, we recognize that the control the focal company formally exerts on suppliers is inevitably affected by the relative bargaining power between firms.
(Casciaro & Piskorski, 2005). A powerful supplier may, in fact, deviate from the buyer prescriptions. This is particularly salient when the buyer makes decisions that are detrimental for the supplier. Thus, we include in our model the relative power of the focal company on its suppliers to control for this effect. Specifically, we account for the fact that a supplier can veto the decision made by the focal company and by the first-tier supplier, if such a decision is detrimental for its own performance. Once the focal company and the first-tier supplier have decided their vectors of decisions, the controlled supplier computes its payoff associated with the new configuration and if the decision is detrimental for its own payoff, the supplier decides to not adopt it and maintain the original choice with a probability depending on the level of relative power of the focal company. A low relative power of the focal company corresponds to a high probability of veto power of the supplier.

Each autonomous supplier changes its own configuration by modifying just one decision. If the new choice assures a higher firm own payoff, the firm adopts it; otherwise, the status quo is maintained. The new configuration of $v_{SN}$ is given by matching the new $v_{FC}$, the new $v_{1stS}$, and the new vectors of the autonomous firms. To generate the new configurations for $v_{FC}$ and $v_{1stS}$, the current configuration of $v_{FC}$ and $v_{1stS}$ is altered by modifying a number of decisions at random ($ALT$). One configuration is chosen at random among all possible ones.

This process is repeated a number of times. In the end, the SN-adaptive performance is computed by the fitness of the last SN configuration, measured in terms of the percentage of the highest SN performance. Notice that at the end of the simulation time, the SN may reach the highest peak or could be stuck in one of suboptimal configurations. It will depend on the scope of control, which affects the search strategy and the ruggedness of the fitness landscape. The overall flow chart for the simulation process including the operationalization of the main constructs and control variables is presented in Figure 2.

**Operationalization of the Variables**

The *scope of formal control* is operationalized by considering the number of searching agents (focal company, first-tier supplier, and upstream suppliers) and the number of decisions each agent controls. The *level of relative power* of the focal company on the supplier is operationalized in terms of the probability that the supplier will veto the decision made by focal company or by the first-tier supplier, if the decision is detrimental for its own local performance. The *complexity* of the SN is modeled by the number of decisions ($N$) and the average number of supply interactions ($K$). The *SN-adaptive performance* is operationalized by the payoff of the SN configuration at the end of the search process, computed as a proportion of the highest payoff that is achievable.

**SIMULATION ANALYSIS**

**Baseline Model**

The baseline model of this study is developed using empirical data coming from a real-world SN. This allows us to capture complexity of the SNs by means of empirically based values of $N$, $K$, and influence matrix. The data cover the entire
SN from raw material suppliers to a focal firm involved in the production of an automobile “center console” assembly. The SN corresponds to the Accord’s product line managed by Honda and the data were collected in 2016 (Figure 3).

We collected data for the material flow network and the contractual relationship network, as described in Choi and Hong (2002). The material flow network describes which supplier delivers materials and parts to which buyer. The nodes are the firms, and the ties are the supply relationships between them. Thus, the material flow network is used to assess the parameters of SN complexity, i.e., $N$, $K$, and the influence matrix. In particular, $N$ corresponds to the number of firms (nodes) in the network and $K$ to the average number of supply relationships (ties) among them. In particular, $K$ means that, on average, each firm in the SN has $K-1$ material flow connection. The influence map is obtained by translating each tie linking $a$ with $b$ in the material flow network with an “$x$” between $a$ and $b$ in the influence matrix. In particular, the “$x$” in a cell of the influence matrix means that the firm in the row is supplied by the firm in the column. Thus, the influence matrix corresponds to the material flow in the SN. The influence matrix of the Accord’s SN is shown in Figure 4. Note that it corresponds to the pattern of interactions named “dependent” by Rivkin and Siggelkow (2007). This is characterized by the existence of one or few decisions influenced by many others (e.g., $d_2$), whereas other decisions (i.e., $d_3$–$d_{16}$) are autonomous.

Data obtained from the material flow network show that the number of firms ($N$) in the SN for Accord is 16. The corresponding average number of supply interactions ($K$) is 2. This means that each firm in the SN has, on average, one material flow link. To identify the scope of formal control, we collected
data concerning the contractual relationship network. The contractual relationship network describes the contractual relationships that exist in the SN. Here, the nodes are the firms, and the tie-connecting node $a$ (the buyer) with node $b$ (the supplier) is the contractual agreement through which the node $a$ controls the node $b$ (Kim, Choi, Yan, & Dooley, 2011). The contractual relationship network contains information on how much of the SN is formally controlled by the focal firm and
first-tier supplier. We consider that a lower tier supplier (e.g., a fourth-tier supplier) is “controlled” when it has a contractual agreement with either the focal firm or first-tier supplier. A lower tier supplier is considered autonomous when there is no contractual agreement with the focal firm or the first-tier supplier, but only with the buyer in the adjacent tier (i.e., the third tier), because this means that its decision is outside the control of the focal firm. The supplier makes the decision for itself by following local rules. The contractual relationship network for the Accord is presented in Figure 5.

We compute: (i) the number of nodes controlled by the focal firm, (ii) the number of nodes controlled by the first-tier supplier, and (iii) the nodes that are under control by neither the focal firm nor the first-tier supplier. The nodes controlled by the focal firm are determined by identifying all nodes in the contractual relationship network that are linked with the focal firm. The percentage of controlled nodes by the focal firm is the measure of the scope of formal control directly exerted by the focal firm. The nodes controlled by the first-tier supplier are determined by identifying suppliers that are linked with the first-tier supplier in the contractual relationship network. All other nodes, under the control of neither the focal firm nor the first-tier suppliers, are regarded as firms that are under no control.

Honda directly controls first-tier supplier and four upstream suppliers, and the first-tier supplier controls 10 upstream suppliers. As to our model, the focal company (firm 1) makes its own decision \((d_1)\) and the decisions of the firms coded with 2, 11, 12, 13, and 14, so that \(v_{FC} = (d_1, d_2, d_{11}, d_{12}, d_{13}, d_{14})\). The first-tier supplier makes the decisions of the firms coded from 3 to 10, 15, and 16. Thus, \(v_{1stS} = (d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}, d_{15}, d_{16})\).

Finally, we collected information concerning the relative power of the focal company as compared to all suppliers. We asked Honda to rate the level of relative bargaining power with its supplier using a Likert scale from very low (1) to very high (5). On average, the level of relative power of the focal company on the suppliers is quite low (1.87). Honda has a very high relative power (5) over the first-tier supplier, a high power (4) over one of the second-tier suppliers, a moderate
Figure 6: The Accord’s SN average performance over time.

or low level (3 or 2) relative power over four suppliers, and a very low relative power (1) over the remaining suppliers. The scale was normalized to define the probability of veto power for the supplier.

The baseline model is run for 100 periods. Simulation is then replicated over 300 landscapes; each randomly generated using the procedure described in the previous section. We collected the SN performance at the end of simulation time, computed as a portion of the highest payoff achievable on the landscape. Results are then averaged across all the 300 landscapes. The evolution of SN performance is shown in Figure 6. The average SN performance increases over time as the SN configuration changes, until it reaches a stationary value. The final SN average performance is 0.9628 (SD .0305). This value corresponds to the adaptive performance of the SN characterized by $N = 16$ and $K = 2$ and in which the scope of control is 100%.

SIMULATION RESULTS

To investigate our conceptual model, we designed experimental scenarios by changing the scope of control exerted by the focal company, the level of supply interactions ($K$), and the number of firms ($N$). In particular, we designed nine scenarios with the scope of control ranging from 20% to 100% by decreasing the number of searching agents and consequently increasing the number of firms formally controlled by the focal company and first-tier supplier. For example, when the scope of control reduces to 93%, there is an additional searching agent (the firm 14) and the focal company controls one decision less ($d_{14}$) compared to the scenario with 100% scope of control. When the scope of control reaches the value of 20%, there are 12 further searching agents, corresponding to firms coded from
5 to 16. In such a case, the focal company makes only two decisions—for itself ($d_1$) and the first-tier supplier ($d_2$)—while the first-tier supplier makes decisions $d_3$ and $d_4$. All the other decisions are made by autonomous suppliers. In total, we consider nine variants of scope of control in the SN (see the Appendix).

To analyze the effect of the level of supply interactions ($K$), we considered five values of $K$, ranging from 2 to 6. We did not simulate experiments with higher $K$, because even though they are theoretically possible, they would correspond to SNs whose material flow networks result in interconnections that are in contrast with empirical observations. The experiments with higher $K$ are defined by generating new fitness landscapes, one for each $K$ value. The influence matrix of the new fitness landscape was built by adding to the baseline influence matrix ($K=2$), the required number of supply interactions in random chosen positions. An additional “x” in the cell of the influence matrix means a material flow connection between the firm in the row (buyer) and the firm in the column (supplier).

Finally, in addition to the $N=16$ within the base case, we consider two additional SNs with $N=18$ and $N=14$. We limited $N$ to 18, because higher values of $N$ increases the computational size of the problem by the order of $2^N$. Lower levels of $N$ were not included because they correspond to SN with a limited number of firms. To identify the influence matrices corresponding to the new scenarios with $N=14$ and $N=18$, we started with the baseline influence matrix (with $N=16$) and created new SNs comprising of $N=14$ (by removing two suppliers) and $N=18$ (by adding two suppliers). In particular, in the case of $N=14$, we removed the last two suppliers (Channel prime and Toray). Then, we defined the influence matrices corresponding to increasing $K$ values (i.e., 3, 4, 5, and 6) by following the same procedure that was used for $N=16$. Similarly, in the case of $N=18$, we added two suppliers to the baseline influence matrix, and assumed that one of them directly supplies Honda and the other one supplies the first-tier supplier (see the influence matrix for $N=18$ and $K=2$), so that the material flow network closely relates to the empirically observed one. Then, we defined the influence matrices for the other values of $K$ with the same procedure above. The influence matrices of all experiments are shown in the Appendix.

Effect of the Scope of Control on SN Performance

We first analyze the effect of formal control on SN performance. Table 2 shows SN average performance for $N=16$ as the scope of formal control ranges from 20% to 100% and $K=2$. The difference between each pair of results is tested by means of a t-test. Most of the pairs are significantly different from each other, except when indicated otherwise in the table.

Notice that the SN performance first increases as the scope of formal control grows but then decreases, as the scope of formal control further increases, irrespective of the level of $K$. For example, SN performance increases from 0.9508 to 0.9823 as the scope of formal control grows from 20% to 86%, but then decreases to 0.9156 when control reaches 100%. This result lends support for our Hypothesis 1.

The result suggests that some scope of formal control is good but too much can hurt SN-adaptive performance. When the scope of formal control is too low, the SN is managed by multiple decision makers who optimize their local performance
Table 2: Average performance for increasing scope of control and $K$ ($N = 16$).

<table>
<thead>
<tr>
<th>Scope of Formal Control</th>
<th>20%</th>
<th>33%</th>
<th>47%</th>
<th>60%</th>
<th>73%</th>
<th>80%</th>
<th>86%</th>
<th>93%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K = 2$</td>
<td>0.9508</td>
<td>0.9751</td>
<td>0.9769</td>
<td>0.9778</td>
<td>0.9777</td>
<td>0.9823</td>
<td>0.9768</td>
<td>0.9628</td>
<td></td>
</tr>
<tr>
<td>$K = 3$</td>
<td>0.8943</td>
<td>0.9029</td>
<td>0.9049</td>
<td>0.9218</td>
<td>0.9274</td>
<td>0.9259</td>
<td>0.9258</td>
<td>0.9156</td>
<td></td>
</tr>
<tr>
<td>$K = 4$</td>
<td>0.8435</td>
<td>0.8684</td>
<td>0.8830</td>
<td>0.8847</td>
<td>0.8967</td>
<td>0.9063</td>
<td>0.8961</td>
<td>0.8962</td>
<td>0.8592</td>
</tr>
<tr>
<td>$K = 5$</td>
<td>0.7777</td>
<td>0.8068</td>
<td>0.8116</td>
<td>0.8292</td>
<td>0.8398</td>
<td>0.8565</td>
<td>0.8321</td>
<td>0.8379</td>
<td></td>
</tr>
<tr>
<td>$K = 6$</td>
<td>0.7034</td>
<td>0.7555</td>
<td>0.7698</td>
<td>0.7717</td>
<td>0.7991</td>
<td>0.8249</td>
<td>0.8202</td>
<td>0.8077</td>
<td>0.8021</td>
</tr>
</tbody>
</table>

$SD$                                                                                              

| $K = 2$ | 0.0395 | 0.0381 | 0.0219 | 0.0220 | 0.0226 | 0.0211 | 0.0185 | 0.0168 | 0.0305 |
| $K = 3$ | 0.0637 | 0.0640 | 0.0646 | 0.0592 | 0.0483 | 0.0432 | 0.0426 | 0.0444 | 0.0649 |
| $K = 4$ | 0.0837 | 0.0659 | 0.0708 | 0.0663 | 0.0686 | 0.0629 | 0.0669 | 0.0573 | 0.0797 |
| $K = 5$ | 0.1064 | 0.0381 | 0.0924 | 0.1134 | 0.0925 | 0.1008 | 0.0929 | 0.0791 | 0.0941 |
| $K = 6$ | 0.1177 | 0.0381 | 0.1141 | 0.1220 | 0.0991 | 0.0919 | 0.0974 | 0.1088 | 0.0860 |

Note: $t$-Test is not significantly different between 73% and 80% scope of control with $K = 2$ and between 86% and 93% level of with $K = 4$. All the other SN performances are significantly different from each other at $p < 0.0001$. FC makes decision by itself and the first-tier in all scenarios.

rather than pursue the improvement of overall SN performance. Such an approach neglects all the interdependencies existing among SN firms and limits the alignment of the conflicting goals among firms so that SN performance suffers. As the scope of formal control increases, the centralized effort accomplished by the focal company enables handling of the interdependencies and resolution of the conflicting goals of partnering firms. This improves SN performance. However, when the scope of control becomes too high, despite the possibility to overcome conflicting aims, the SN performance decreases, because the adaptive process becomes ineffective. In particular, very high scope of formal control reduces the ability of the system to explore the landscape. For example, when the scope of formal control is equal to 100% or 93%, the adaptive process is performed by only one or two searching agents, who can explore the landscape less than three or four searching agents, such as when the scope of formal control is 86% or 80%. Note that the highest SN performance is achieved when the scope of formal control is equal to 86%. This value provides the best trade-off in terms of centralized effort required to resolve conflicting aims and number of searching agents needed to explore the landscape.

The Effect of Complexity Dimensions

Results in Table 2 also show that as $K$ increases, the average SN performance decreases, irrespective of the scope of formal control. For example, with a scope of formal control equal to 100%, as $K$ increases from 2 to 3, the SN performance diminishes from 0.9628 to 0.9156, while for $K = 4$, $K = 5$, and $K = 6$ the SN performance decreases to 0.8592, 0.8379, and 0.8021, respectively. This confirms our Hypothesis 2a concerning the negative effect of the level of supply interactions on SN performance. As $K$ rises, the firms are more interconnected with each other. This implies that the SN is characterized by a higher number of
conflicting goals and suboptimal configurations (local peaks), where exploration may be trapped. This reduces the efficacy of the adaptation process and lowers SN performance.

Next, we analyzed results for $N = 18$ and $N = 14$ with $K = 2$ (see Tables 3a and 3b). To investigate the effect of increasing the number of firms on SN performance, we compared results achieved by averaging SN performance across different scope of control (last column in Tables 3a and 3b).
Table 4: Performance difference between $K = 2$ and $K = 6$.

<table>
<thead>
<tr>
<th>Performance difference</th>
<th>Scope of Formal Control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td>24.74%</td>
</tr>
</tbody>
</table>

Note: All the other SN performances are significantly different from each other at $p < .001$.

Table 5: Performance difference between $N = 14$ and $N = 18$ for the same scope of control.

<table>
<thead>
<tr>
<th>Performance Difference</th>
<th>Level of Formal Control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>23%</td>
</tr>
<tr>
<td>$K = 2$</td>
<td>4.84%</td>
</tr>
<tr>
<td>$K = 3$</td>
<td>4.45%</td>
</tr>
<tr>
<td>$K = 4$</td>
<td>3.67%</td>
</tr>
<tr>
<td>$K = 5$</td>
<td>1.68%</td>
</tr>
<tr>
<td>$K = 6$</td>
<td>0.18%</td>
</tr>
<tr>
<td>Mean</td>
<td>2.96%</td>
</tr>
</tbody>
</table>

Note: All the other SN performances are significantly different from each other at $p < .001$.

Note that as $N$ rises from 14 to 18, SN performance decreases, For example, the SN performance decreases from 0.97615, to 0.91843, as $N$ rises from 14 to 18. This confirms our Hypothesis 2b concerning the negative effect of the number of firms on SN performance.

To test Hypothesis H3a, we computed the performance difference between $K = 2$ and $K = 6$, the extreme values of $K$ considered in the experiments (Table 4). We can note from Table 4 that this performance difference is affected by the scope of formal control. The lowest value of performance difference (15.28%) is achieved for a moderately high value of formal control (80%) and the highest value of performance difference (24.74%) is achieved when the scope of formal control is very low (20%). This outcome confirms that in the presence of high complexity due to high level of interrelationships (i.e., high $K$), moderate-high scope of formal control offers a better approach, because it enhances the adaptive behavior of the SN. For low values of scope of control, the system is not able to handle the interdependencies and, as $K$ grows, the likelihood of being trapped in suboptimal configurations increases. The result lends support to our Hypothesis H3a concerning the moderating effect of the scope of control on the relationship between the supply interactions and SN performance.

To test Hypothesis H3b, we compare the performance difference between $N = 14$ and $N = 18$, the extreme values of $N$ considered in the experiments, for the same value of formal control (Table 5). For example, for the scope of formal control equal to 100%, the SN performance decreases from 0.9890 to 0.8864 as $N$ rises from 14 to 18. Similarly, for a scope of formal control equal to 23% and $K = 2$, SN performance diminishes from 0.9740 to 0.9256 as $N$ moves from 14 to 18. We note that, on average (last row in Table 7), the performance difference grows as
the scope of control increases. For example, it is 2.96% when the scope of control is equal to 23%, 3.12% when the scope of control is equal to 46%, 3.31% when the scope of control is equal to 62%, and 5.65% when the scope of control is equal to 100%. This means that, with higher values of scope of control, as the number of firms in an SN increases, the decrease in SN performance is more. Increasing \( N \) requires improved SN decision-making capability due to the higher number of decisions to be made by the focal firm and its first-tier supplier who acts on the focal firm’s behalf. This lends support for Hypothesis H3b that the negative effect of number of firms on SN performance depends on the scope of formal control.

**Validation**

In developing our hypotheses, we are uncertain about the boundary conditions, i.e., all the contexts for which the accuracy of the theoretical predictions is high (Busse, Kach, & Wagner, 2017). Thus, we need to explore them so as to extend the validity of our theory. Among the possible approaches to do this, we use the inside-out approach (Busse et al., 2017). This means to explore the validity of the theory outside the range of the empirical context that formed the basis for this study. The empirical context corresponds to the baseline case, which is characterized by the console manufacturing in the automotive industry, a moderate number of firms \((N = 16)\) in the SN, a low level of interaction \((K = 2)\), and a low power of the focal company on suppliers (on average 1.87). We validate our findings by controlling for context-delineating variables (Busse et al., 2017). Given the scope of the study, we are limited in terms of the empirical data that come from a specific industry context; however, we consider several variants of SN to examine the boundary conditions. Specifically, we run simulation models by considering different values for the number of firms in the SN \((N)\), level of interactions among firms \((K)\), and the relative power of the focal firm.

We use the data that we collected by simulating the entire plan of experiments. These data were obtained by setting the level of relative power of the focal company to 1.87, i.e., the empirical value by Honda. Because we need to control the results for this variable, we performed further simulations in three additional conditions: (i) the scenario where the focal company has a very low power over all suppliers, except for the first-tier supplier (on average 1.27), (ii) the scenario in which the focal company has a symmetric relative power over all suppliers (on average 3.13), and (iii) the scenario in which the focal company has a very high relative power over all suppliers (on average 5).

Using the data obtained from experimental scenarios, we run regression models. First, we test Hypothesis 1 after controlling for the effects of the number firms \((N)\), the level of supplier interactions \((K)\), and the relative power of the focal company on suppliers. We test the effect of a complexity dimension (i.e., \( K \) in Hypothesis 2a and \( N \) in Hypothesis 2b), after controlling for the other dimension and the relative power of the focal company so as to discern their partial effects on SN performance. Finally, we test Hypotheses 3a and 3b after controlling for the scope of control, complexity, and the relative power of the focal company.

The results of the regression models are presented in Table 6. We find support for Hypothesis 1: the positive significant beta coefficient for control (Model 5:
Table 6: Regression analyses for the effect on SN performance.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>.985625**</td>
<td>1.05578**</td>
<td>1.17382**</td>
<td>1.09261**</td>
<td>1.11133**</td>
</tr>
<tr>
<td></td>
<td>(0.00963)</td>
<td>(0.00041)</td>
<td>(0.0004)</td>
<td>(0.00814)</td>
<td>(0.01967)</td>
</tr>
<tr>
<td>Relative Power</td>
<td>.00039</td>
<td>.00038</td>
<td>.00039</td>
<td>.0001</td>
<td>.0001</td>
</tr>
<tr>
<td></td>
<td>(0.00052)</td>
<td>(0.00048)</td>
<td>(0.00040)</td>
<td>(0.0004)</td>
<td>(0.00039)</td>
</tr>
<tr>
<td>N</td>
<td>-.00737**</td>
<td>-.00737**</td>
<td>-.00743**</td>
<td>-.00266*</td>
<td>-.00266*</td>
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<tr>
<td></td>
<td>(.000405)</td>
<td>(.00048)</td>
<td>(.00046)</td>
<td>(.00122)</td>
<td>(.00122)</td>
</tr>
<tr>
<td>K</td>
<td>-.04704**</td>
<td>-.04704**</td>
<td>-.04704**</td>
<td>-.07080**</td>
<td>-.07080**</td>
</tr>
<tr>
<td></td>
<td>(.003641)</td>
<td>(.00769)</td>
<td>(.00035)</td>
<td>(.00095)</td>
<td>(.00095)</td>
</tr>
<tr>
<td>CONTROL</td>
<td>.23270**</td>
<td>.20760**</td>
<td>.23866**</td>
<td>.13904**</td>
<td>.13904**</td>
</tr>
<tr>
<td></td>
<td>(0.01143)</td>
<td>(0.02892)</td>
<td>(0.00915)</td>
<td>(0.00896)</td>
<td>(0.00896)</td>
</tr>
<tr>
<td>CONTROL^2</td>
<td>-.13886**</td>
<td>-.13904**</td>
<td>-.13904**</td>
<td>-.13904**</td>
<td>-.13904**</td>
</tr>
<tr>
<td></td>
<td>(0.00915)</td>
<td>(0.00896)</td>
<td>(0.00896)</td>
<td>(0.00896)</td>
<td>(0.00896)</td>
</tr>
<tr>
<td>N*CONTROL</td>
<td>-.00757**</td>
<td>-.00757**</td>
<td>-.00757**</td>
<td>-.00757**</td>
<td>-.00757**</td>
</tr>
<tr>
<td></td>
<td>(0.00166)</td>
<td>(0.00166)</td>
<td>(0.00166)</td>
<td>(0.00166)</td>
<td>(0.00166)</td>
</tr>
<tr>
<td>K*CONTROL</td>
<td>.03661**</td>
<td>.03661**</td>
<td>.03661**</td>
<td>.03661**</td>
<td>.03661**</td>
</tr>
<tr>
<td></td>
<td>(0.00131)</td>
<td>(0.00131)</td>
<td>(0.00131)</td>
<td>(0.00131)</td>
<td>(0.00131)</td>
</tr>
</tbody>
</table>

Model fit statistics

Number of observations: 260000
R-squared: 0.0059
Root MSE: 0.10596
F-statistics: 80.78**
[degrees of freedom] [2] [2] [3] [5] [7]

Note: Standard error in parentheses; degrees of freedom in square brackets; *p < .05; **p < .01.

Table 7: Performance difference between scenarios $N = 14$ & $K = 2$ and $N = 18$ & $K = 6$.

<table>
<thead>
<tr>
<th></th>
<th>23%</th>
<th>46%</th>
<th>62%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N = 14$ &amp; $K = 2$</td>
<td>0.9740</td>
<td>0.9742</td>
<td>0.9739</td>
<td>0.9808</td>
</tr>
<tr>
<td>$N = 18$ &amp; $K = 6$</td>
<td>0.6929</td>
<td>0.7266</td>
<td>0.7659</td>
<td>0.8149</td>
</tr>
<tr>
<td>Difference</td>
<td>28.11%</td>
<td>24.76%</td>
<td>20.80%</td>
<td>16.59%</td>
</tr>
</tbody>
</table>

Note: All the other SN performances are significantly different from each other at $p < .001$.

$\beta_n = 0.20760; p < .01$ and negative significant beta coefficient for control-squared (Model 5: $\beta_{n^2} = -0.1390; p < .01$) indicate that, after controlling for the effects of $N$, $K$, and relative power of the focal company on supplier, there is an inverted U-shaped relationship between the scope of formal control and SN performance. We used Stata’s $u$-test (Lind & Mehlum, 2010) to ensure that our data include the maximum value and to validate the inverted U relationship between control and SN performance. The extreme point of the inverted U-shape relationship between control and SN performance was .838 ($p < .01$; 95% Fieller interval = .809, .874). The values of maximum value as well as the Fieller interval fall within our data set for control ($\mu = .649$, min = .2, max = 1). The results lend support for H2a (Model 5: $\beta_K = -0.07080; p < .01$) and H2b (Model 5: $\beta_N = -0.00266; p < .05$), indicating that after controlling for relative power of the focal firm, $K$ and $N$ are significantly negatively associated with SN performance. Finally, we also find support for H3a and H3b: after controlling for the scope of control, $N$, $K$, and the
relative power of the focal company, the interaction between the scope of control and $K$ is positive (Model 5: $\beta_{c \times K} = 0.03661; p < .01$), indicating that higher scope of control can help in mitigating the detrimental effect of complexity emanating from the level of interactions and the interaction between the scope of control and $N$ is negative (Model 5: $\beta_{c \times N} = -0.00757; p < .01$), indicating that higher scope of control can worsen the detrimental effect of complexity emanating from the number of firms in the SN.

**CONCLUSIONS**

While previous studies on control in SNs mainly focused on buyer–supplier relationships and analyzed the issue of the modes of control to adopt to improve the performance, this study investigated the relationship between the scope of control and performance in a SN context. Our results showed that focal firm should carefully consider how much of the SN to formally control because this choice impacts SN performance. Our main finding is that a moderate scope of control results in higher SN performance than when the scope of control is either too high or too low. Controlling a right number of suppliers improves coordination and helps in aligning the conflicting goals of supply chain partners, while with no control, coordinated activities become difficult and performance suffers. At the same time, controlling a large number of suppliers may deteriorate SN performance because it constrains the ability of the SN to adapt. Therefore, focal firms should consider allowing some level of autonomy so as to improve the efficacy of adaptation of their SNs.

Our study investigated the influence of complexity of SN, both due to the level of interactions among firms and number of firms, on SN performance. We confirmed previous results of the literature concerning the negative effect of these two complexity dimensions on SN performance (Bozarth et al., 2009; Bode & Wagner, 2015). More interestingly, our study also found that the scope of formal control influences the negative effect of complexity on SN performance. In the case of complexity due to high level of supply interactions, if the scope of control is high (low), SN performance suffers less (more). This also suggests that in networks that are highly interconnected, the focal firm should guide its suppliers toward a coherent direction by means of control. As to the negative effect of the number of firms on SN performance, we found that the higher the scope of control, the higher the negative influence on SN performance. This suggests that when SN complexity is associated with a higher number of firms, less control is beneficial. Our results suggest two different strategies to mitigate the negative influence of complexity. If the source of complexity is the level of supply interactions, more scope of control is needed; if the complexity is due to the number of firms, less scope of control should be applied. We were able to establish the validity of our results by exploring the boundary conditions.

There are a few limitations of the study that provide opportunities for future research. Because we take the approach of empirically informed simulation modeling research, our study uses data from one organization (i.e., Honda) to gain a focused understanding of the role played by various aspects considered in this study, but this limits the validity of results to the specific industry considered. In particular,
our results pertain to an SN concerning console manufacturing in the automotive sector. The generalizability of the results of this study to conditions extending the current ones should be considered in further research. We also acknowledge that our measure of control presents some limitations. We conceptualize control as a binary variable without considering intensity of control. It is not influenced by the tier in which the supplier belongs to and by the fact whether it is the focal firm or the first-tier supplier that exerts control. Finally, due to lack of underlying theory to address the joint effect of both number of firms in the network and the number of interrelationships between firms, we did not explicitly hypothesize their interactive effect on SN performance or the scope of control that would result in higher performance when SN is subject to high $N$ and $K$. However, using the data that we collected, we conducted a post-hoc analysis that might provide directions for future theory-building efforts. Specifically, we compute the performance difference between the scenario with $N = 14$ and $K = 2$ (the lowest complexity jointly captured by both $N$ and $K$) and the scenario with $N = 18$ and $K = 6$ (the highest complexity jointly captured by both $N$ and $K$) for the same levels of formal control (Table 7). The results seem to suggest that the scope of formal control positively influences the performance difference. This implies that in the presence of high complexity emanating from both supply interactions ($K$) and number of firms ($N$), high values of scope of formal control result in a lesser decrease in SN performance than in the presence of low values of scope of formal control. We conjecture that when both $N$ and $K$ are high, the landscape becomes very rugged and multipeaked. In such a case, it is necessary to improve the ability of the system to overcome the local peaks by increasing the scope of control. We believe that further research is needed to gain more in-depth understanding of the joint effect of $N$ and $K$. This presents an interesting opportunity for future research.

REFERENCES


APPENDIX

Description of the Landscape Generation

An exemplar landscape is generated and shown in Table A1 below for \( N = 3, K = 2 \), and the influence matrix shown in Figure A1.

The landscape consists of eight configurations (a–h) described by the vector \( \mathbf{d} = (d_1, d_2, d_3) \) where \( d_i = 0 \) or 1. The decision \( d_i \) in each of the eight configurations gives a contribution \( C_i \) to the system payoff, drawn at random from a Uniform [0, 1] distribution. \( C_i \) models how good the choice on the decision \( d_i \) is for the system.

Given the interactions among decisions, the contribution \( C_i \) of the decision \( d_i \) depends not only on how the decision \( i \) itself is resolved (i.e., 0 or 1), but also on how interacting decisions are resolved. According to the influence matrix in
Figure A1, the decision $d_1$ is affected by the decision $d_2$. Thus, the contribution $C_1$ of the decision $d_1$ is also affected by how $d_2$ is resolved. As a result, $C_1$ is the same in all the choice configurations in which $d_1$ and $d_2$ assume the same value; for example, when both are 0 (i.e., in configurations a and b), the contribution $C_1$ is 0.13. In choice configuration c, even though $d_1$ is 0, as in choice configurations a and b, given that $d_2$ assumes the value 1, a different $C_1$ will be generated by drawing at random from a Uniform [0, 1] distribution.

In the NK model, the landscape is made up of peaks and valleys. Each configuration is a point on the landscape and the overall payoff is the height of the point. Valleys correspond to configurations with low fitness values, while peaks are points with higher fitness. The configuration with the highest payoff is the global peak (d). Suboptimal configurations are the local peaks (i.e., no configuration different in one decision exists with higher payoff).

Depending on the ruggedness of the landscape and the algorithm used to look for the global peak, the system can reach the global peak or may be blocked in the suboptimal configurations. If the system adopts an incremental local searching process, where only one decision at random can be changed, the local peak represents a point that blocks the system’s adaptive walk, because no higher point exists in the neighborhood of the configuration. In this case, the system stops to search. The higher the number of the local peaks, the higher the likelihood that the system can be blocked in these suboptimal configurations and the lower the system performance. In our exemplar landscape in Table A1, the configuration b is a local peak. If the system reaches the configuration b and can move only in adjacent points (i.e., those configurations differing from b in just one decision), it remains blocked in it.

Table A1: Exemplar landscape.

<table>
<thead>
<tr>
<th>Conf.</th>
<th>Vector</th>
<th>Contributions</th>
<th>Payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0 0 0</td>
<td>0.13 0.34 0.96</td>
<td>0.48</td>
</tr>
<tr>
<td>b</td>
<td>0 0 1</td>
<td>0.13 0.68 0.96</td>
<td>0.59</td>
</tr>
<tr>
<td>c</td>
<td>0 1 0</td>
<td>0.57 0.76 0.34</td>
<td>0.56</td>
</tr>
<tr>
<td>d</td>
<td>1 0 0</td>
<td>0.54 0.34 0.87</td>
<td>0.65</td>
</tr>
<tr>
<td>e</td>
<td>1 1 0</td>
<td>0.40 0.68 0.87</td>
<td>0.58</td>
</tr>
<tr>
<td>f</td>
<td>1 0 1</td>
<td>0.54 0.76 0.08</td>
<td>0.46</td>
</tr>
<tr>
<td>g</td>
<td>0 1 1</td>
<td>0.57 0.49 0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>h</td>
<td>1 1 1</td>
<td>0.40 0.49 0.08</td>
<td>0.32</td>
</tr>
</tbody>
</table>

Figure A1: Influence matrix.
Influences Matrices of the Experiments

N=16

K=3

K=4

K=5

K=6
Operazionalization of the Different Values of Scope of Control
## The Impact of Control and Complexity

### Scope of Control

<table>
<thead>
<tr>
<th>No. of searching agents</th>
<th>20%</th>
<th>33%</th>
<th>47%</th>
<th>60%</th>
<th>73%</th>
<th>80%</th>
<th>86%</th>
<th>93%</th>
<th>100%</th>
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<td>N = 16</td>
<td>14</td>
<td>12</td>
<td>10</td>
<td>8</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Controlled decisions by FC</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2/3–10</td>
<td>1–2/3–10</td>
<td>1–2/11</td>
<td>1–2/11–12</td>
<td>1–2/11–13</td>
<td>1–2/11–14</td>
</tr>
<tr>
<td>Independent decisions</td>
<td>5–16</td>
<td>7–16</td>
<td>9–16</td>
<td>11–16</td>
<td>11–14</td>
<td>12–14</td>
<td>13–14</td>
<td>14</td>
<td>–</td>
</tr>
<tr>
<td>N = 18</td>
<td>14</td>
<td>13</td>
<td>11</td>
<td>8</td>
<td>6</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Controlled decisions by FC</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2/11</td>
<td>1–2/11–13</td>
<td>1–2/11–14</td>
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<tr>
<td>Independent decisions</td>
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<td>7–18</td>
<td>10–18</td>
<td>11–16</td>
<td>11–14</td>
<td>12–14</td>
<td>14</td>
<td>–</td>
<td></td>
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<tr>
<td>$N = 14$</td>
<td>23%</td>
<td>31%</td>
<td>46%</td>
<td>62%</td>
<td>77%</td>
<td>85%</td>
<td>92%</td>
<td>100%</td>
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<td>------</td>
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<tr>
<td>No. of searching agents</td>
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<td>11</td>
<td>9</td>
<td>7</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Controlled decisions by FC</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2</td>
<td>1–2;11</td>
<td>1–2;11–12</td>
<td>1–2;11–13</td>
<td>1–2;11–14</td>
<td></td>
</tr>
<tr>
<td>Controlled decisions by first-tier supplier</td>
<td>3–4</td>
<td>3–5</td>
<td>3–7</td>
<td>3–9</td>
<td>3–10</td>
<td>3–10</td>
<td>3–10</td>
<td>3–10</td>
<td></td>
</tr>
<tr>
<td>Independent decisions</td>
<td>5–14</td>
<td>6–14</td>
<td>8–14</td>
<td>10–14</td>
<td>12–14</td>
<td>13–14</td>
<td>14</td>
<td>–</td>
<td></td>
</tr>
</tbody>
</table>

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