How Partnership Behaviour Evolves in Networks: Path Dependency, Social Figuration and Life Events

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Abstract

Networks have become the dominant life form in many organizational settings. Most studies of relationships in networks focus on the dyadic interaction between two agents. However, work on enactment, sensemaking, path dependency, and social figuration processes (by Weick, Elias, and others) suggests that complex networks cannot be exclusively understood in terms of dyadic relationships. This paper therefore explores emergent processes of enactment and sensemaking in network settings by means of an agent-based model. In particular, we develop an agent-based model of a two-tiered supply network of ten firms with heterogeneous dispositions towards partnership. This model serves to explore the interaction between disposition, sensemaking and behaviour in a network. The simulation results exhibit strong path dependency effects and, in a highly stylised manner, capture the emergent process of enactment and retrospective sensemaking. An important finding is that path dependency effects occur in response to so-called life events (e.g. a calamity that disrupts the flow of products). Our findings also imply that inner dispositions may not determine the actual behaviour emerging over time in complex and turbulent (supply) networks. This raises questions regarding network research that focuses on dyadic relationships studied by means of cross-sectional data.

NOTE: Please use a color printer to print (the Figures in) this manuscript. Several figures are more easily read and interpreted in a full-color version.

Introduction

> In March 2000 "a fire at a Philips Electronics plant in Albuquerque, New Mexico, disrupted the flow of chips to cellphone makers Nokia Corp. and Ericsson. Both competitors depended solely on Philips for these particular chips and were equally affected by the fire, but their reactions were very different. Nokia invoked a special process developed for such situations, putting Philips and the chip on a special 'watch list'. Nokia engineers then called Philips daily to inquire about the situation. It became clear very quickly that the fire was a major disruption and the plant would be out for months. Nokia responded aggressively, sending 30 employees to work with Philips and other suppliers to restore supply. It also used different manufacturers, designed its handsets to use different chips where possible and secured Philips' entire worldwide capacity for manufacturing the chips it needed. Nokia's CEO communicated directly with Philips' CEO about the problem on a regular basis.
>
> Ericsson, by contrast, was not proactive and did not realize the seriousness of the disruption until weeks later. By the time it mounted a recovery effort, the worldwide supply of the chips in question – from Philips and other suppliers – was committed to Nokia. Nokia achieved its sales plans; Ericsson missed a critical new product introduction that resulted in an estimated $400 million revenue loss. Not long after, Ericsson ceased making cellular phones under its individual brand" (Sheffi and Rice 2005: 47-48).

Networks have become the dominant life form in many business settings (cf. Fine 1998; Klein Woolthuis, Hildebrand and Nooteboom 2005; Koza and Lewin 1999). By means of their supply networks, original equipment manufacturers (OEMs) such as Ericsson and Nokia source their materials and subassemblies from a large number of suppliers (including Philips in the case above). Each firm in this type of network has specific preferences for doing business with its various counterparts. However, it is unclear how those preferences are formed. Path dependency effects occurring throughout the formation stage of the network may complicate the picture. Moreover, the Nokia versus Ericsson case previously outlined suggests that the dispositions of the senior managers of firms participating in the network matter. These dispositions may differ in terms of their proactiveness, resilience and time horizon (Sako 1992; Dyer and Ouchi 1993; Dyer 1996; Bensaou 1999; Sheffi and Rice 2005). Indeed, the generative conditions and processes producing (discontinuities in) collaborative behaviour are very complex. The number of possible factors that needs to be taken into account may simply be too great to be studied with conventional empirical methods.

In this paper computer simulation serves to explore the generative processes behind the evolution of partnership behaviour in networks. We develop a simulation model of a supply network of five OEMS, who receive materials from five suppliers and serve a single end markt. In this model, supply network partnerships emerge from a network of OEMs and suppliers with initially undifferentiated, identical preferences for doing business with other parties. This model serves to explore whether the dynamics of partnership preferences in such a supply network are characterized by path dependency, social figuration (cf. Elias 1998) and life events (cf. Holmes and Rahe 1967).

Through simulation experiments with this type of model "unexpected consequences of the interaction of simple processes" can be discovered (Harrison et al. 2007: 1239). The simulation experiments discussed in this paper imply the following unexpected patterns. First, it appears that path dependency effects do not start from Day 1 of the network but rather from D-day (e.g., the fire at the Philips Electronics plant that disrupts the flow of chips to Nokia, Ericsson and other firms). D-days are moments in time when relations in the network become severely stressed (so-called life events). We also find that there is a considerable time delay involved between the moment that these stressful life events occur and the time when differentiation in partner preferences becomes apparent. Moreover, the simulation experiments show that lock-in effects (Arthur 1994; Shapiro and Varian 1999) do occur in these networks: the same 'life event' that leads to a major disruption in preferences during the formative stages of the network does not lead to major changes when it occurs once preferences have become stable. Finally, we show that internal dispositions of network actors have little predictive value for actual behaviour of these actors over time. Rather than their internal dispositions, it seems to be the social figuration (Elias 1998) arising from their complex interactions that determines if they display more short-term rather than long-term oriented behaviour.

The simulation experiments discussed in this paper suggest that a supply network – and more generally, any network – can be conceptualized as a complex adaptive system in which path dependency effects play a critical part in driving partnership behaviour, but for which it is problematic if not impossible to predict ex ante what these effects will be (cf. Kaufmann 1995; Axelrod 1997; Brown and Eisenhardt 1998; Holland

1998). Rather than claiming that these phenomena are bound to occur, we argue that the experiments yield what Axelrod (1997) has called 'existence proofs': that is, these simulations show that it is *possible* for supply networks to produce these types of behaviour (cf. Harrison et al. 2007).

As such, this paper challenges and extends the conventional wisdom by developing a simulation model of the emergence of partnership behaviour in large networks. In particular, we focus on the interaction between disposition towards collaboration with other firms and actual partnership behaviour in supply networks. In this respect, sociologists have argued that dispositions and preferences are almost by definition unobservable (e.g. Elias 1998), whereas others have pointed out that collaboration involves enactment as a process of social construction (e.g. Weick 1979).

The argument is organized as follows. First, the theoretical background of the argument as well as the method adopted is outlined. We then describe the model and use it to simulate the emergence of collaborative behaviour over time in a supply network. Finally, the simulation results and their implications will be discussed.

Theoretical Background

In the last few decades many supply chains have increasingly become supply *networks*, composed of many independent or semi-independent companies. Within these networks, firms tend to collaborate with only a limited number of other firms. Japanese companies pioneered with partnership in the automobile industry, where it became known as co-makership (Ahmadjiam and Lincoln 2001; Dyer 1996; Sako 1992). Subsequently, many partnerships in the aircraft, automobile, computer and other industries have also been engaging in collaborative planning and forecasting (Aviv 2001; Raghunathan 1999). More recently, various new types of R&D partnerships have emerged in the supply chain of pharma-biotechnology and other industries (Chesbrough 2003).

Several theories serve to explain and understand collaboration in the context of networks and alliances. In this respect, the prevailing theoretical frameworks are transaction cost and social exchange theory (e.g. Bensaou and Anderson 1999; Czaban, Hocevar, Jaklic and Whitley 2003; Young-Ybarra and Wiersema 1999). The key object in both theories is the transaction or exchange relationship (e.g. between supplier and producer). As such, these studies primarily look at the *dyadic* relationships between suppliers and buyers, also by largely drawing on cross-sectional data rather than tracking how broader patterns of collaboration arise over time.

Moreover, most studies of transactions in networks draw on notions such as opportunism, flexibility, trust, and learning (e.g. Bensaou and Anderson 1999; Klein Woolthuis et al. 2005; Mayer and Argyres 2004; Simonin 2004). The largely implicit assumption here is that dispositions – regarding flexibility, trust, and so forth – are key drivers of the actual partnership behaviour of firms embedded in large networks (e.g. Klein Woolthuis et al. 2005; Tomlinson 2005). As such, the notion of partnership itself appears to be very ambiguous, due to the tensions between trust and power within inter-organizational relationships (cf. Czaban et al. 2003; Tomlinson 2005).

Elias (1998) argues that a complex network can be understood in terms of a dyadic game involving agent A and B, in which A reacts to B's action in a certain way (or any other game with a relatively small number of agents). He observes that even in a game involving only two actors it may be impossible to derive attitude from behaviour because the interactions involved are simply too complex. He argues that inner motivations and dispositions (attitudes) cannot be derived from the outward behaviour of actors – be they individuals, groups or organizations. According to Elias, the *social figuration* of these actors determines their behaviour. For instance, he reflects on the interpretation of the twelfth move of an actor in a hypothetical game involving two persons as follows:

> We are inclined to interpret this move in terms of the character of the person who made it. (….) any of these explanations might be justifiable but none of them is sufficient. For the twelfth move in such a game can no longer be adequately explained in terms of short, unilinear causal sequences. Nor can an explanation be based upon the individual character of one or the other player. This move can only be interpreted in the light of the way the preceding moves of both players have intertwined, and of the specific figuration which has resulted from this intertwining (Elias 1998: 136).

This problem is reinforced in the case of a network consisting of two or more echelons and a larger number of actors in each echelon. Elias' argument implies that the observation of long-term partnership behaviour implies very little about actors' actual dispositions, at any given time.

At a more fundamental level, Weick (1979) argues that collaborative processes in a system involving a large number of human agents are characterized by ambiguity, enactment and retrospective sensemaking. Being concerned with these emergent processes means that

> "one is attuned to sequences, unfolding, generative settings, amplification, and small events with large consequences. Small beginnings generate unanticipated consequences, as is argued by people who adopt complexity theory. But those small beginnings often don't stay small. They change size, constrain other events, and spread through what others reify into groups, organizations, and institutions" (Weick 2004: 664).

Previous studies of partnership and inter-organizational collaboration largely ignore the emergent nature of enactment and sensemaking processes. An exception is Tomlinson's (2005) case study, which suggests that trust and other dispositions cannot be simply assumed but arise from communicative activities over time.

In the remainder of this paper we develop and simulate a model of an archetypical supply network to explore the temporal complexity of partnership behaviour in supply networks. In this respect, the *main questions* are as follows:

- can processes of enactment, sensemaking and social figuration in large (supply) networks be represented and simulated in an agent-based model?
- what kind of – possibly path dependent – interactions occur between the agents in this model; in other words, what kind of patterns and consequences do these interactions give rise to?

Method

We apply agent-based modelling to partnership behaviour in large networks for several reasons. First, the need to collect longitudinal data on entire networks over a longer period complicates empirical studies in this area (Kenis and Knoke 2002), particularly in view of the immensely complex patterns of interactions in these networks. Moreover, empirically investigating preferences and dispositions is notoriously difficult. People may not know why they do or have done things (and firm representatives may not know why their firms behave in particular ways in the networks they are part of); moreover, they may be reluctant to reveal their real motivations (Flick 1998). In this respect, a growing body of evidence suggests that survey data about preferences and perceptions may be severely biased (see for overview of studies in this area: Mezias and Starbuck 2003; Starbuck 2006).

Agent-based simulation can address these issues effectively. An agent-based model can represent the dispositions, preferences and internal decision rules of many agents (Axelrod 1997; Holland 1995; Kauffman 1995). Moreover, it serves to understand properties of complex systems through the analysis of the data generated by simulations with the model. Agent-based modelling provides the opportunity to *assume* certain dispositions for a number of agents and then *observe*, by running the simulation model for a certain period of time, the patterns that emerge from the interaction between agents.[1]

In this respect, agent-based modelling involves elaborate thought experiments to learn about (real world) complex adaptive systems, rather than to build a valid representation of the real system (Axelrod 1997; Holland 1995). This modelling approach serves to discover unexpected consequences of the interaction of (in themselves) rather simple processes (Harrison et al. 2007). As such, attempts to statistically validate an agent-based model by means of data on the real system tend to be largely futile (Lomi and Larsen 2001). The simulation experiments in this paper are therefore designed to explore what would happen if a number of actors, with their internal decision rules and position in the network, locally interact over time. As such, we are interested in the emergent properties, as large-scale effects of locally interacting agents, of the entire supply network.

In the model discussed in more detail in the next section, the internal decision rules of each agent are modelled by means of a system dynamics model. That is, the decision-making processes at the individual agent (firm) level are defined as a set of differential equations and, subsequently, a ‘bottom-up’ agent-based approach is adopted to model the interaction between agents (Sterman 2000).[2] This approach implies that the utility-maximizing premise – often used in mathematical models – is replaced by less restrictive positive feedback mechanisms characterized by self-interest and self-reinforcement, as suggested by Sydow, Schreyögg and Koch (2005).

As recommended in the literature, the model was developed in a number of steps (Coyle 1996; Richmond 2001; Sterman 2000): development of initial model, simulation of steady state conditions, simulation experiments (e.g. with a one-time or permanent change in one particular variable), and sensitivity analysis of the findings obtained with these experiments. This implies that all simulation findings reported later in this paper were tested for their sensitivity towards small changes in initial conditions and experimental inputs. Moreover, we also controlled for sensitivity towards structural characteristics of the model (e.g. whether it involves a 3 x 3, 5 x 5 or 10 x 10 supply chain). The detailed documentation on all equations in the model as well as the simulation experiments is available from the authors.

Model

This section describes the structure of the simulation model to explore answers to the research questions described earlier. We adopt the following definitions of partnership, disposition, and preference:

- *Partnership* involves stable and durable relationships with a small number of partners (Dyer and Chu 2003).
- *Disposition* refers to the generic, rather inert, attitude the firm's management has towards a certain issue (e.g. partnering with others). The definition of partnership disposition, a key element of the model, follows from the previous definitions.
- *Preference* denotes the psychological state (i.e. cognitive and affective) towards a particular entity (e.g. a certain supplier). Preferences are therefore linked to specific entities, whereas dispositions are related to more abstract ideas and concepts. The formation of preferences is a critical element of the sensemaking process in the model.
- *Behaviour*, in terms of the actual actions taken (e.g. placing an order at a particlar supplier), can therefore be conceptually distinghuished from dispositions and preferences.

Moreover, we do not assume any unidirectional causal relations between disposition, preferences and behaviour. Rather, the model starts from the assumption that dispositions are rather inert at the individual (firm) level and that patterns in preferences and behaviour emerge over time from the numerous local interactions between firms in the network.

The firms in the model interact by ordering component materials with their suppliers and shipping products to their buyers. These firms differ from each other in two ways. First, they have different positions in the network. Second, firms have different partnership dispositions. Adding more business processes (e.g. R&D) and heterogeneity (e.g. different dispositions with regard to risk) would make the model more realistic but also severely complicate the analysis and interpretation of simulation results.

The model contains 1728 variables, and was developed in *Vensim* software (www.vensim.com). The complete model documentation is available from the authors. The remainder of this section provides an overview of the structure of the model and some key relationships.

Structure of the Network

The simulation model represents a supply network of five OEMs, who receive materials from five suppliers and who jointly serve a single end markt. In this model, the partnership dispositions of buyers and suppliers are differentiated. All other starting conditions – for example, market shares, inventory levels and other operational characteristics – are identical for all firms. In this section we describe the model's structure, particularly those aspects of the model that drive its overall behaviour: the key feedback loops linking the agent's preferences for and performance towards its counterparts (for both suppliers and OEMs). Figure 1 provides a causal loop diagram that depicts the feedback loop which, in a variety of manifestations, determines overall behaviour in the network. This diagram shows how the preferences of two actors in the network mutually influence each other over time. We will start from the top, with the rectangle "*Existing preference of supplier A for customer B*". The use of a rectangle denotes that this is an accumulation over time, a so-called stock variable in system dynamics terminology (Sterman 2000). This preference is a number between 0 and 1, which indicates what portion of overall supply this supplier A is willing to allocate to customer B. Therefore, the greater this preference, the greater will be the value of "*Allocation of A's resources to B*". (In a causal loop diagram, this positive correlation is shown by the "+" next to the head of the arrow connecting the two variables in Figure 1.)

Insert Figure 1 about here

The greater the latter allocation, the better that A will be able to meet B's demand ("*Ability by A to meet B's demand*"). The greater this ability, the more positive agent B will perceive A's delivery performance ("*Perception by B of A's current performance*"). The more positive this perception, the more positive the *current* preference for A by B becomes. However, in the overall assessment of its preference for A, agent B also assesses the performance by A in the past. In psychological terms, the anchor-and-adjustment heuristic (Northcraft and Neale 1987; Russo and Schoemaker 1989; Sterman 2000) is adopted here: how B perceives A is based on a long-term perception grounded in the past (the "anchor") with modifications for current discrepancies with that long-term perception (the "adjustments"). How much of the past is taken into account, is a function of the internal disposition of the agent: does the agent take a more long-term or short-term time horizon of the value of the relationship? In the model, this is implemented by a "*Perception adjustment delay of B*". In formal terms:

Change in B's Perceptions = (Current preference – Existing preference of B for A) / Perception Adjustment Delay of B

(Note that the *Existing* Preference is the actual preference as a response to cumulative performance over time, whereas the *Current* Preference responds to the most recent performance of the agent's counterpart.)

How large this perception adjustment delay is, will be determined by the "*Partnership disposition of A*", which is one of the few areas in the model where individual actors differ. We will return to this notion shortly.

We now turn to the bottom of the diagram, moving upwards again by following the loop in a counter-clockwise manner. The "*Existing preference of B for A*" drives the "*Allocation of B's orders to A*": The more that B likes A, the more that B will order from A, or, the higher the "*Order volume from B to A*" will be. The more that B orders with A, the more A will like B. Hence, the higher "*Perception by B of A's current performance*" and, in conjunction, "*Current preference of A for B*" will be. Similar to the preference-setting process for B, supplier A's preferences are determined by an anchor-and-adjustment process. So, again, the "*Perception adjustment delay of A*" determines how quickly the "*Existing preference of A for B"* will be adjusted to A's current preference for B. And again, this adjustment delay is driven by the Partnership disposition, this time of B.

A critical point here is that the same logic applies to all OEMs and all their relations. Although this is a single feedback loop, in a model of five suppliers and five OEMs, it occurs 5x5=25 times, as every supplier has a mental image of every customer and vice versa. Moreover, all these feedback loops interact. When A prefers to ship materials to one particular customer, he will ship less to the others, which tends to make him less popular with these other OEMs.

In this respect, what happens to one supplier-customer relation in the network affects all others. If, for instance, A prefers B but B is also preferred by other suppliers (i.e. the "*Delivery performance of other suppliers with B*" is high), then B may not increase its preference towards supplier A, because A's competitors are serving B equally well or even better. In turn, this delivery performance depends on several other factors, including the "*Overall ability of the supply base to meet customer demand*". This overall volume of customer demand also plays a role in the degree to which OEM A and its competitors perform towards the supply base: The smaller the "*Size of B's overall demand*", the less B can allocate to A. And the greater the "*Size of order volume of other customers*", the greater the order volume that they will place with A, which will negatively affect A's perception of B.

Partnership Dispositions and Preferences for Customers and Suppliers

A key concept in the model is *partnership disposition*, operationalised in the "Preference adjustment delay", as discussed above. This disposition involves the extent to which a firm (i.e. its senior managers) values stable and durable relationships with suppliers or buyers. Each of the 10 firms differs with regard to the partnership disposition (its management has) towards suppliers α^S or the partnership disposition towards their customers α^C. Both parameters range between 0 and 1 and refer to how important stable and durable (supplier respectively customer) relationships are perceived to be for the firm. For example, if a supplier has a partnership disposition of 0.8, this implies that the preference for any customer is determined for 20% by its recent performance and for 80% by the long-term history of engaging in business with this firm, that is, the cumulative orders placed or shipments delivered. For both the customer group and the supplier group, the distribution of α^S and α^C is the same. Table 1 depicts this distribution.

Insert Table 1 here

The key feedback loop described in Figure 1 is a straightforward model of the firm's sense-making process, in terms of the formation of *preferences* for specific customers or suppliers. Theoretically speaking, this part of the model is based on Arthur's (1993; 1994) 'learning automaton', implying that in each period agents update their preferences for all suppliers and customers. They do this on the basis of the information received regarding the consequences of their past preferences. In other words, agents *learn* from their unique experiences. In this respect, the partnership disposition determines how quick a particular preference changes. Firms thus react directly to changes in the behaviour of customers and suppliers, and indirectly to changes in the behaviour of their competitors. In other words, a certain partnership disposition implies a particular speed of change.

Simulation Experiments: Findings

This section turns to simulation experiments with the model of a supply network described previously. In particular, the experiments with this simulation model serve to explore whether the dynamics of partnership preferences in such a supply network can indeed be characterized by path dependency, social figuration, and life events – as discussed earlier in this paper. In the remainder of this section we discuss four behavioural characteristics of the model:

1. path dependency effects occur in response to 'life events' in the network;

2. path dependency effects are subject to considerable time delays;
3. lock-in effects occur, as agents' preferences freeze over time;
4. inner dispositions towards partnership have little predictive value for actual behaviour.

All simulation experiments reported in this section start from a steady state situation in which all in- and outflows are equal and therefore stock levels are constant over time. These initial conditions allow for a laboratory setting, in which all patterns of behaviour occuring over time in the simulation experiment can be traced back to one particular change.

In the remainder of this section we will illustrate the main findings in terms of the interaction between supplier 1 and its five customers. Of the five suppliers, supplier 1 has the weakest partnership disposition (see Table 1). That is, it highly values the current performance (in terms of orders received) of a customer and places relatively little value on the historical ties it may have with that customer. Please note that each of the four main findings reported on the next few pages applies to all suppliers and all customers in the network represented in the model.

Path dependency effects occur in response to "life events" in the network

Simulation runs with the model suggest that path dependency effects do not start from Day 1 of the network, but rather from D-day, an episode in which relations in the network become severely stressed. This is illustrated in Figure 2. In this simulation scenario, end market demand is stable until it suddenly peaks for 5 weeks in time period 100. This simple experiment yields interesting results. Figure 2 shows the preferences of and for one actor in the model, in this case supplier 1, who has a relatively short time horizon regarding partnerships. The left graph shows how the preferences of supplier 1 for OEMs 1 to 5 evolve from fully undifferentiated to a rather chaotic pattern after 2.5 years (125 weeks) until a stable distribution of preferences is reached after ten years (500 weeks). Similarly, the right graph in Figure 2 shows how the preferences of the five OEMs in the model evolve from undifferentiated at 0.2 to highly preferred by OEM 1, more preferred by OEMs 1, 3 and 4, and fairly unchanged for OEM 2. In this scenario, supplier 1 gets at least his proportional share (20% of the business) relative to his competitors, suppliers 2, 3, 4 and 5.

An important point to be made, however, is that major changes in the network dynamics initiate path dependency effects. These major changes are labelled as 'life events', in analogy with the psychological literature (cf. Holmes and Rahe 1967). So, we suggest that path dependency does not start from Day 1 but rather from D-Day, from the time that major pressures require real choices to be made.

Insert Figure 2 about here

Path dependency effects are subject to considerable time delays

With regard to the former finding, it is also relevant to observe that these path dependency effects are subject to significant time delays. The sudden peak of 40% more market demand happens at the end of the first year, after 50 weeks. And yet Figure 2 shows that it takes the supply network another year and a half to transform the consequences of this demand increase into differentiated partner preferences. Evidently, the length of this delay results from the structure of the model (i.e. the time delays in the feedback loop in Figure 1). A closer look at the values, rather than the graph, shows that differences in the partner preferences start to develop almost immediately after the demand pulse but remain relatively insignificant for quite some time.

Lock-in effects freeze preferences over time

After the “chaotic” period of 2.5 to 10 years, it appears that the distribution of preferences freezes (cf. Kaufmann 1995). In economic terms, lock-in effects (Arthur 1994; Shapiro and Varian 1999) have then occurred in the network. This can be illustrated by experimenting with the same life event at different stages of the development of the network.

Suppose that, as a result of a calamity, supplier 1 loses all its work-in-progress and final inventory in a single week and is thus not able to ship materials (cf. the fire at Philips Electronics that disrupts the flow of materials to cellphone OEMs). In addition to the base case (without a calamity), we can simulate the model according to two scenarios: in the first scenario the calamity occurs in week 50 (after one year) and in the other scenario in week 500 (after ten years). The response by OEMs to the early calamity scenario is shown in Figure 3. We already know how the preferences of the customer base developed over time in the base case, as that is visualised in the right-hand side of Figure 2. Figure 3 shows major fluctuations in preferences after one year, as a result of supplier 1's sudden problems with inventory and delivery. However, if the calamity occurs after 10 years, the output is almost identical to the right-hand graph of Figure 2: preferences have completely frozen, and the calamity does not create major changes in preferences in the network. (HENK: we hebben hier afzonderlijk ook deze simulatie in een Figuur nodig. Volstaat niet om te verwijzen naar vorige Figuur 2, als zijnde ongeveer hetzelfde. Kun je dus de simulatie zoals in Figuur 3 doen, maar dan met de calamity na 10 jaar.) In other words, the calamity that leads to a major disruption in preferences during the formative stages of the network does not lead to major changes when it occurs once preferences have stabilized.

Insert Figure 3 about here

A similar behavioural pattern can be observed in response to a broad range of exogenous demand rate variations, for example also with a sustained oscillation in demand that represents an industrial business cycle. In all these experiments, initially, identical preferences begin to differentiate in the aftermath of a critical event in the supply network; subsequently, preferences move into a chaotic phase during which they can change in any direction; finally, they stabilize in a differentiated pattern. A key finding therefore is that, after the life event has set things in motion, it is not primarily (the initial or any other) external event that drives the further evolution of preferences. Rather, the *internal* reinforcing feedback loops that have been invoked in the network determine the structure of the emerging partnerships.

Inner dispositions towards partnership have little predictive value for actual behaviour

Finally, the simulation experiments suggest that internal dispositions of network participants may have little predictive value for actual behaviour in a supply network over time. Figure 3 suggests it is the customer with the strongest long-term orientation, OEM 5, who changes her preferences for supplier 1 most drastically. On the other hand, all OEMs, regardless of their partnership orientation, become fixed in their preferences in the long run, also the ones with a short term orientation. The same holds for supplier 1, who also is highly short-term oriented yet becomes fixed in his preferences in the long run.

A more important observation with regard to Figure 3 is that, in the long run, supplier 1 performs reasonably well after this major calamity. OEM 1's preference for this supplier is considerably greater than in the base case, and although he is less-than-average preferred by OEM 2, the three other OEMs still have a preference for him that exceeds 20%. This is a counter-intuitive finding, but one we also observed repeatedly in other experiments with this model.

Discussion

The agent-based model in this paper was developed to explore whether processes of enactment, sensemaking and social figuration in large networks can be represented and simulated in a mathematical model; and in addition, which findings from simulation experiments possibly extend our understanding of these complex processes in networks. The simulation findings discussed in the preceding section point to the complex, and indeed inherently chaotic nature of the behaviour of the supply network during the simulation experiments. Due to the countless interactions of the agents involved, one cannot predict *ex ante* their future behaviour or infer how successful they will be from their initial preferences. In line with Elias (1998), this suggests it is the social figuration of the agents that arises out of their complex interactions – rather than their internal dispositions – which determines whether the behaviour of agents displays more short-term rather than long-term (collaborative) orientations.

The Philips-Ericsson-Nokia case discussed at the beginning of this paper serves to illustrate this. The fire at the Philips plant is evidently a critical life event in the formation of collaborative ties with customers. In terms of the simulation results described in the preceding section, the partnership ties between Nokia and Philips are reinforced enormously as a result of the calamity in the Philips plant – similar to supplier 1 and customer 5 in the simulation reported in Figure 3. In the simulation run as well as in the reality of the case, the customer (Nokia) responds aggressively by putting the supplier (Philips) on a special watch list, by sending over employees, and so forth. As such, the customer's preference for this supplier breaks down almost immediately (see Figure 3), but is then quickly restored as a result of the collaborative effort to restore supply.

Also as a result of the close ties developing between supplier 1 and customer 5 (Philips and Nokia), the supplier fails to restore trust of, for example, customer 2 (e.g. Ericsson). The model does not allow firms to leave the network; moreover, a minimum performance of the supplier prevents that the preference of customer 2 for supplier 1 completely breaks down.

In sum, we suggest that dispositions regarding partnership may be rather loosely coupled to the actual behaviour emerging over time. The simulation results imply that all firms, regardless of their very different (inert) dispositions, act in a rather non-collaborative manner during the defining stages of the network. At later stages all firms tend to shift to partnership-like preferences and behaviour, again regardless of their dispositions. In this respect, preferences for specific suppliers and buyers adapt to behavioural patterns observed by the firm (cf. retrospective sensemaking). Moreover, at critical intervals, characterized by life events, the local interactions between firms produce systemic transitions in the network that cannot be controlled by any firm or group of firms. Behavioural and sensemaking patterns *before* and *after* these intervals appear to be fundamentally different. As such, the model appears to effectively capture the path dependent processes of social figuration, enactment and sensemaking outlined earlier in the paper.

In this respect, the notion of critical (life) event may serve to extend our understanding of the effects of path dependency. The literature typically defines path dependency in terms of 'history matters' as well as self-reinforcing processes characterized by positive feedback (e.g. Schreyögg and Kliesch-Eberl 2007; Sydow et al.

2005). This implies that the entire history of a particular network – in terms of its past behaviour and performance – provides an imprint for its current and future development. The experiments with the simulation model in this paper suggest that the path dependent processes initiated by critical life events prevail over other events and processes. The fire at the Philips Electronics plant that disrupted the flow of chips to Nokia, Ericsson and other firms is a good example of such a critical event. The notion of critical life events may thus help to extend the emerging theory of path dependency.

In more general terms, we assumed that the structural dynamics of collaboration in any large network over a longer period of time arises from the local interactions between participants in the network. These dynamics can be understood in terms of path dependency and lock-in effects. Dispositional constructs regarding, for example, partnership, trust and risk may be relevant for explaining micro-level differences between individual firms, but they appear to be largely *irrelevant* for explaining (changes in) structural patterns of behaviour at the level of the entire network. Moreover, a systemic agent-based explanation of the dynamics of partnership patterns in networks also extends the literature that explains partnership behaviour by looking at changes in the competitive structure and other contingencies (as independent variables).

An important implication for future research is that dispositions may not affect the actual behaviour emerging over time in complex and turbulent (supply) networks. In this respect, our model suggests all firms *regardless* of their disposition towards partnership tend to display more non-partnership behaviour during the formative period of the network and tend to exhibit rather stable patterns of partnership behaviour later on. This raises questions regarding research that exclusively focuses on the micro-relationship between supplier and buyer across a rather short time span. Simulation modelling is therefore an important complementary tool in any attempt to understand what drives behaviour over time in networks composed of a large number of agents.

Limitations

Evidently, the model involves a highly stylised representation of reality. The model assumes limited heterogeneity among firms and thus highly simplifies the (unique) economic, social, political, cognitive and affective processes at the level of the individual firm. In this respect, the heterogeneity of agents is limited to their location in the network and their partnership disposition. However, the more complex and heterogeneous an agent-based model becomes, the more difficult it will be to analyse and interpret simulation results.

As such, this type of simulation model can not substitute methods currently prevailing in partnership research (e.g. ethnographic fieldwork and surveys) but is a complementary tool. In particular, the longitudinal and systemic perspective in agent-based modelling may serve to reframe and generalise findings from studies of dyadic relationships between firms.

Concluding Remarks

We explored whether emergent processes of enactment and sensemaking in large networks can be represented and simulated in an agent-based model; and what can be learned from the simulation results obtained with this model. In particular, the impact of different kinds of partnership dispositions on the sensemaking process around preferences for suppliers or customers in supply networks is modelled. The model involves a stylised two-stage supply chain of five suppliers, five OEMs and a final customer market. The firms in this network differ in terms of their location in the supply chain as well as their disposition towards long-term partnerships with suppliers or customers.

The main findings are as follows:

- path dependency effects occur in response to 'life events' in the network;
- path dependency effects are subject to considerable time delays;
- lock-in effects occur as agents' preferences freeze over time;
- inner dispositions towards partnership have little predictive value for actual behaviour.

An important implication for future research is that dispositions may not affect the actual behaviour emerging over time in complex and turbulent (supply) networks. This raises questions regarding research that exclusively focuses on the micro-relationship between supplier and buyer across a rather short time span. As such, simulation modelling may be an important complementary tool in any attempt to understand what drives collaborative behaviour over time in large networks.

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Figure 1: Key Feedback Loop

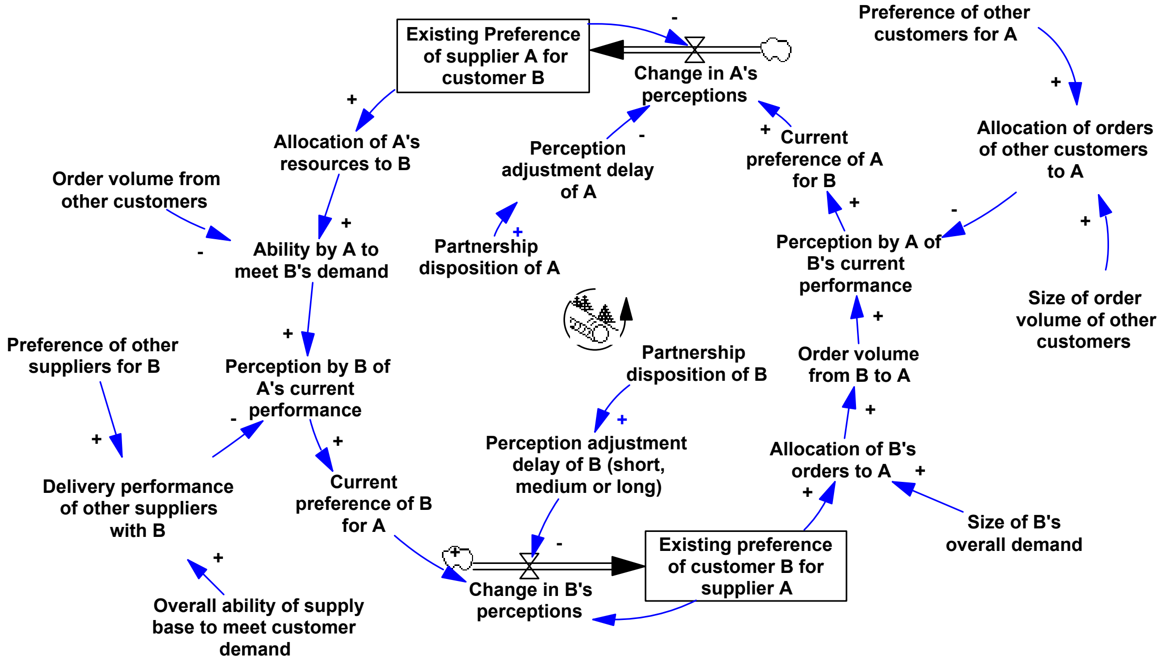

Table 1: Preference Distribution In Terms of Long-Term versus Short-Term Performance of Its Suppliers and Customers

(e.g. $\alpha = 0.75$ implies a weight of 0.75 for LT cumulative performance and 0.25 for ST performance)

Supplier	Customer Preference α^C	OEM (Customer)	Supplier Preference α^s
1	0.2	1	0.2
2	0.4	2	0.4
3	0.6	3	0.6
4	0.8	4	0.8
5	1.0	5	1.0

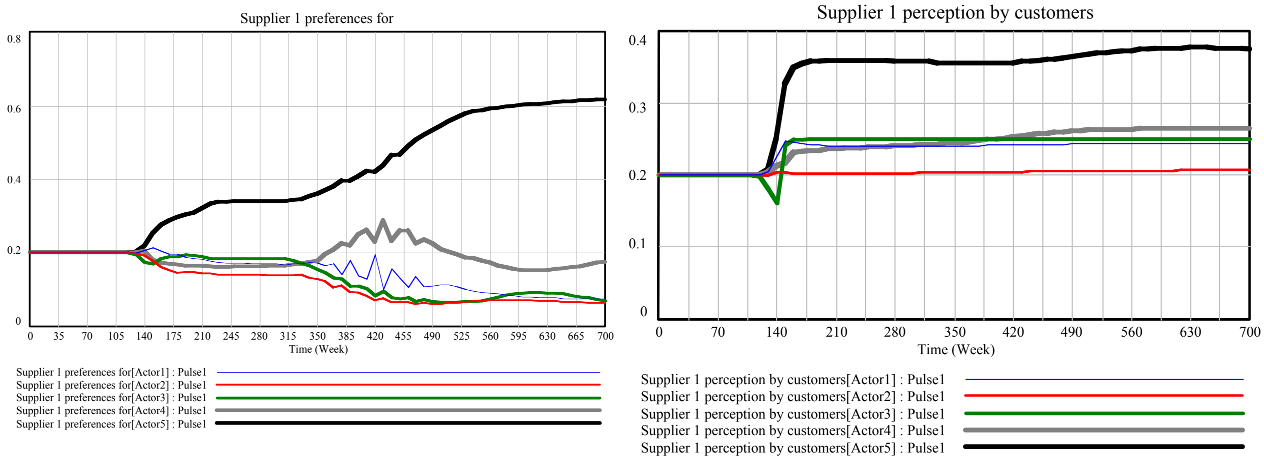

Figure 2: Evolution of Preferences of Supplier 1 for Customers 1 to 5 and Evolution of Preferences of Customers 1 to 5 for Supplier 1 after a One-Time Pulse in Demand

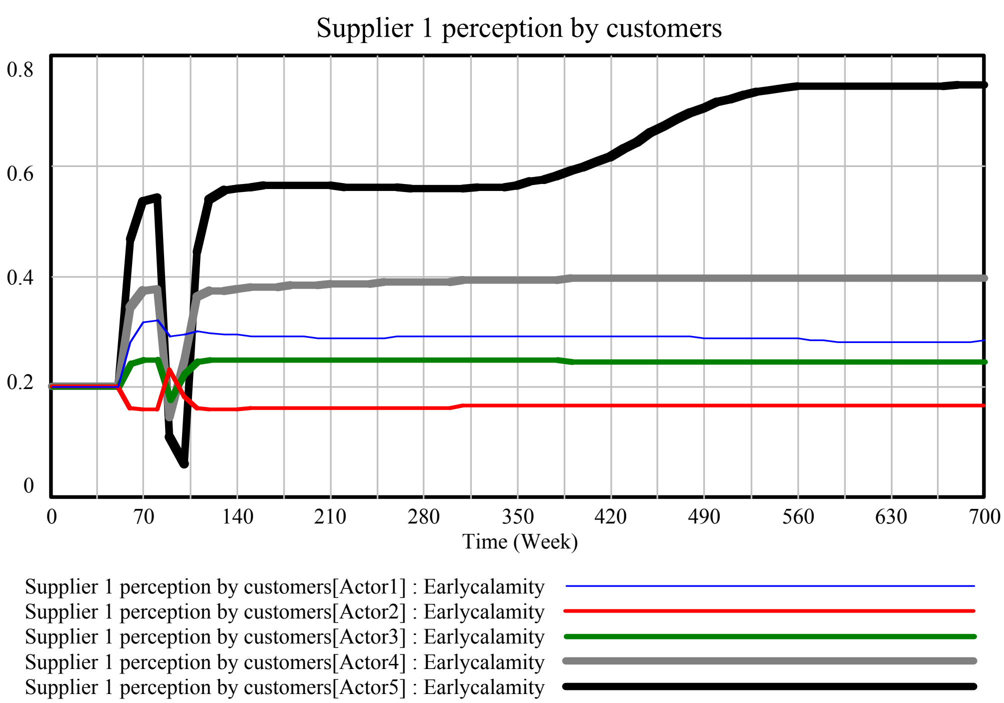

Figure 3: Evolution of preferences of Customers for Supplier 1 after a calamity in Year 1

Endnotes

1 In this respect, agent-based modeling has been developed to overcome some of the fundamental problems of doing research in the social sciences. Simon (1996) has argued that the social sciences are in fact the 'hard' sciences because social and economic processes are not neatly decomposable into separate sub-processes, but are closely interrelated and therefore inherently complex. Controlled experiments are therefore hard to conduct in the social sciences, particularly with regard to the following type of questions: if the behavior of x actors is A and the behavior of y actors is B, what kind of properties will the system these actors are part of exhibit over time? (Axelrod 1997; Holland 1995; Kauffman 1995; Resnick 1994).

2 Dooley (2002) distinguishes between system dynamics and agent-based modelling as two different approaches to simulation. However, Rahmandad and Sterman (2004) show that in many conditions the dynamics produced by agent-based and differential equation models are quite similar. Indeed, both approaches can be effectively integrated (cf. Sterman 2000).