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

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Abstract

Supply networks have become the dominant life form in many business settings. Most studies of relationships in networks focus on the dyadic interaction between two agents and draw on notions such as opportunism, flexibility, trust, and learning. However, work on enactment, sensemaking, path dependency, and social figuration processes (e.g. by Weick and Elias) suggests that complex networks cannot be exclusively understood in terms of dyadic relationships. This paper therefore explores, first, whether emergent processes of enactment and sensemaking in large networks can be represented and simulated in an agent-based model; and second, what can be learned from simulation results obtained with this type of model. We develop an agent-based model of an archetypical network, involving a three-tiered supply chain composed of hundred firms with heterogeneous dispositions towards partnership. This model serves to explore the interaction between disposition, sensemaking and behaviour in a network setting. The model is used to simulate the dynamics over extended periods of time. The simulation results exhibit strong path dependency effects and capture the emergent process of enactment and retrospective sensemaking – although in a highly stylised manner. Our findings also suggest that inner dispositions may not determine the actual behaviour emerging over time in complex and turbulent (supply) networks. This raises questions regarding research that exclusively focuses on dyadic relationships over a rather short time span.

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

Networks have become the dominant life form in many business settings. In for example a supply network, multiple Original Equipment Manufacturers (OEMs) may source their production materials and subassemblies from a large number of suppliers (Fine 1998; Lynn 2005). Each actor in these networks has specific preferences for doing business with its various counterparts. However, it is unclear how those preferences are formed. Is this a matter of path dependency effects occurring throughout the formation stage of the network or do other factors also come into play? What is the importance of the dispositions of the actors with regard to their time orientation – a long or short time horizon – long stereotyped as the "Japanese" vs "the U.S. model" (Sako 1992; Dyer and Ouchi 1993; Dyer 1996; Bensaou 1999)? Moreover, we do not know to what extent these preferences are stable, or, what determines their degree of stability. The number of possible factors to be taken into account is simply too great to be studied with conventional empirical methods.

In this paper we employ computer simulation to explore the generative processes behind these complex phenomena. 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 model, we discover several "unexpected consequences of the interaction of simple processes" (Harrison et al. 2007: 1239). First, it appears that path dependency effects do not start from Day 1 of the network but rather from D-day, the 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 in this paper 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 trust and actual partnership behaviour in very large 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 (Dyer 1996; Nishiguchi 1994; 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; Young-Ybarra and Wiersema 1999). The key object in both theories is the transaction or exchange relationship (e.g. between producer and distributor). As such, these studies primarily look at the *dyadic* relationships between suppliers and buyers and largely draw 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 (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 three or more echelons and a large 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 that 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, difficulties in collecting longitudinal data on entire networks over a longer period complicate 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: 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 as well as the large number of local interactions between these agents (Axelrod 1997; Holland 1995; Kauffman 1995). This type of model can help understand properties of complex systems through the analysis of the data generated by simulations with the model. It 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 many agents.[1]

In this respect, agent-based modelling involves doing elaborate thought experiments to learn about (real world) complex adaptive systems, rather than building a valid representation of the real system (Axelrod 1997; Holland 1995). It serves to discover the unexpected consequences of the interaction of rather simple processes (Harrison et al. 2007). Thus, attempts to statistically validate an agent-based model by means of data on the real system are 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 structure of a particular 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.

The internal decision rules of each agent are modeled 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]

The model was developed in several steps, as recommended in the literature (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 impulses. Moreover, we also controlled the findings 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.

The Model

This section describes the structure of the simulation model developed to explore answers to the research questions described earlier. We adopt the following definitions. *Partnership* involves stable and durable relationships with a small number of partners (Dyer and Chu 2003). The term *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.

The sensemaking process in the model involves the formation of preferences. The term *preference* is used here to denote 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. Evidently, dispositions and preferences are both (conceptually) distinct from *behaviour*, the actual actions taken.

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 would 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, preferences of buyers and suppliers for doing business with each others are initially undifferentiated. Similarly, market shares, inventory levels and other operational characteristics are identical for all firms. Full model documentation is available from the authors upon request. This section describes the model's structure, particularly those aspects of the model that really drive its overall behaviour: its key feedback loops that link preferences for and performance towards the counterparts (for both suppliers and OEMs).

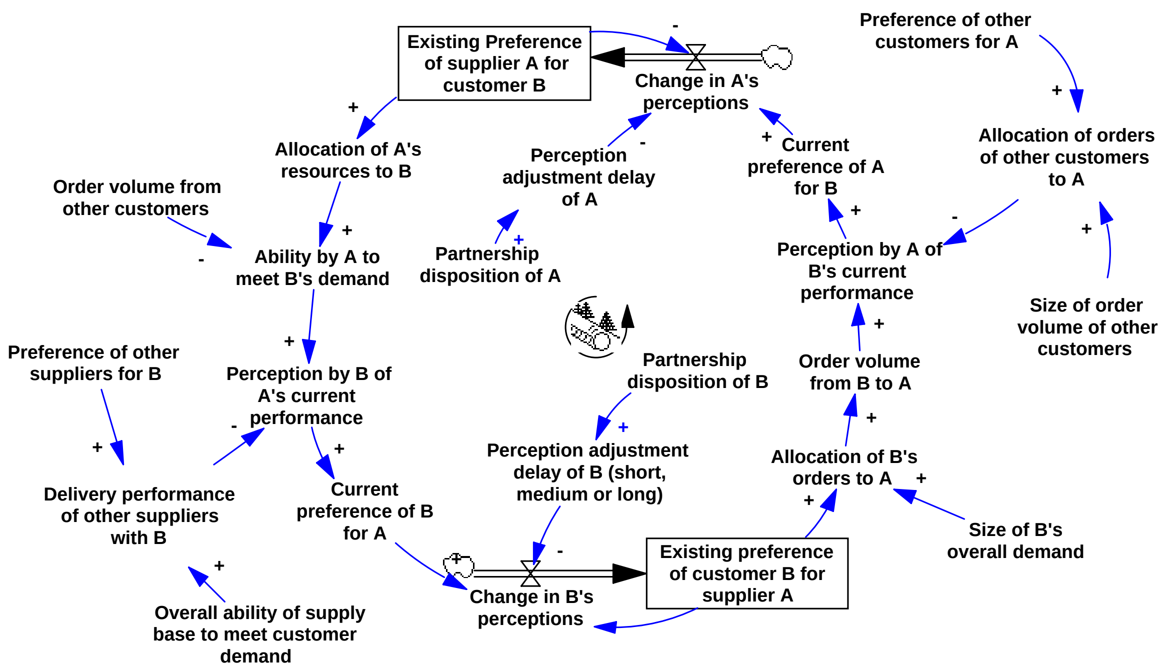

Figure 1: Key feedback loop governing overall model behaviour

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 actors in the network *mutually influence each other over time*. We will start from the top, the rectangle that reads: "<u>Existing preference of supplier A for customer B</u>". The use of a rectangle denotes that this is an accumulation over time, a so-called "stock" or "state 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 "<u>Allocation of A's resources to B</u>". (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.)

The greater the latter allocation, the better that A will be able to meet B's demand ("<u>Ability by A to meet B's demand</u>"). The greater this ability, the more positive agent B will perceive A's delivery performance ("<u>Perception by B of A's current performance</u>"). 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:

$$Change\_in\_Bs\_Perceptions = \frac{Current\_preference\_of\_B\_for\_A - Existing\_preference\_of\_B\_for\_A}{Perception\_adjustment\_delay\_of\_B}$$

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.

Meanwhile, we are now at the bottom of the diagram. From there, we move upwards again, 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 5 suppliers and 5 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. This will make him less popular with these other OEMs.

In this manner, 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. This delivery performance in turn depends on a host of other factors, for instance on 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 "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 as well as the partnership disposition towards their customers α^C. Both parameters range between 0 and 1 and refer to how important stable and durable (supplier and customer) relationships are perceived to be for the firm. For both the customer group and the supplier group, the distribution of α^S and α^C is the same. Table 1 describes this distribution.

As such, with regard to supplier as well as customer partnership dispositions, each group contains two agents that emphasize stable long-term relationships. One agent has a partnership disposition of 0.8, which implies that the preference for a specific supplier or OEM 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. Another agent even focuses completely on long-term performance, with a parameter value of 1.0. One of the agents in each group does not perceive durable and stable relationships to be important (with a partnership disposition of 0.2). The two remaining firms use similar weights for both short-term and long-term performance, with values of 0.4 and 0.6. respectively.

Insert Table 1 here

One other way of categorizing the key feedback loop described above is by seeing it as an operationalisation of the firms's sense-making process, in terms of the formation of *preferences* for specific customers and 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 as a 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 perfect laboratory setting, in which all patterns of behaviour occuring over time in the simulation experiment can be traced back to one particular change.

1. Path Dependency effects arise from “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, the end market demand is stable until it suddenly peaks for 5 weeks in time period 100. This simple experiment yields revealing 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 period 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 5 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. Apparently, Supplier 1 does well in this particular scenario, as he gets at least his proportional share (20% of the business) amongst his competitors, Suppliers 2 to 5.

The specific point to be made is, however, that it is major changes in the network dynamics that initiate path dependency effects. We label these major changes “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
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2. Path dependency effects are subject to considerable time delays

In conjunction with the first point, it is also relevant to note 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 model another year and a half to exhibit clearly the consequences of this demand pulse in terms of differentiated partner preferences. Of course, the values rather than the graph suggest small but gradually increasing differences in the values considerably sooner, but these remain at a level of relative insignificance for quite some time.

3. Lock-in effects freeze preferences over time

After the “chaotic” period of 2.5 to 10 years, it appears that the systems "freezes" in its distribution of preferences (cf. Kaufmann 1995). In economic terms, lock-in effects (Arthur 1994; Shapiro and Varian 1999) have then occurred in the network. We can illustrate this by showing that the same life event that would lead 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. Suppose that, as a result of a calamity (e.g. an earth quake, fire or tsunami), Supplier 1 loses all its work-in-progress and final inventory in a single week and is thus not able to ship materials. 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. Now we see major fluctuations in preferences after one year, as a result of Supplier 1’s sudden problems with inventory and delivery. However, if we conduct the same simulation after 10 years, the output is almost identical to the right-hand graph of Figure 2: preferences have completely frozen, and one calamity is no longer sufficient to achieve major changes in preferences in the network.

Insert Figure 3 about here

Incidentally, similar behaviour can be observed in response to a broad range of exogenous demand rate variations, for instance also with a sustained oscillation in demand, resembling an industry business cycle. In all these experiments, we can observe how, initially, identical preferences begin to differentiate in the aftermath of a “life event” in the business, then move into a chaotic phase where preferences can change in any direction, and finally stabilize in a differentiated manner. Therefore, it is important to note that, after the life event has set things in motion, it is not primarily *external* events that drive the further evolution of preferences, but the *internal* reinforcing feedback loops that have been set in motion, that determine the structure of the emerging partnerships.

4. Inner dispositions towards partnership have little predictive value for actual behaviour

Finally, our simulation experiments suggest that internal dispositions of network actors 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%. Indeed a rather counter-intuitive finding, but one that we have also observed repeatedly in other experiments with this model.

Discussion

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 simulated period. 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 that 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 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. In this respect, our findings 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 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 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, 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 whole 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 instead 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 – such as those in the aircraft, automobile and other industries – is modelled. The model involves a stylised three-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 buyers and customers.

The main findings are as follows:

- path dependency effects occur as a 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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Table 1

Table 1: Preference Distribution In Terms of Long-Term versus Short-Term Performance of Its Suppliers and Customers, for Each Group of Agents
(e.g. α = 0.75 implies a weight of 0.75 for LT performance and 0.25 for ST performance)

Agent	Supplier Preference α^S	Customer Preference α^C
1	0.2	0.2
2	0.4	0.4
3	0.6	0.6
4	0.8	0.8
5	1.0	1.0

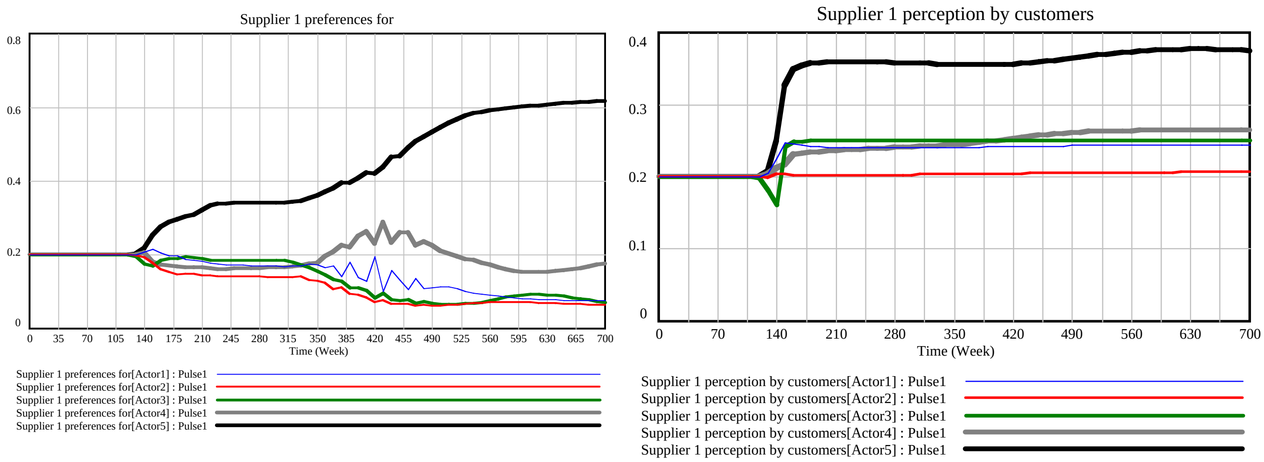

Figure 2: Evolution of preferences of Supplier 1 for Customers 1 to 5, and evolution of preferences of Customers 1 to 5 for Supplier 1 after a one-time pulse in demand

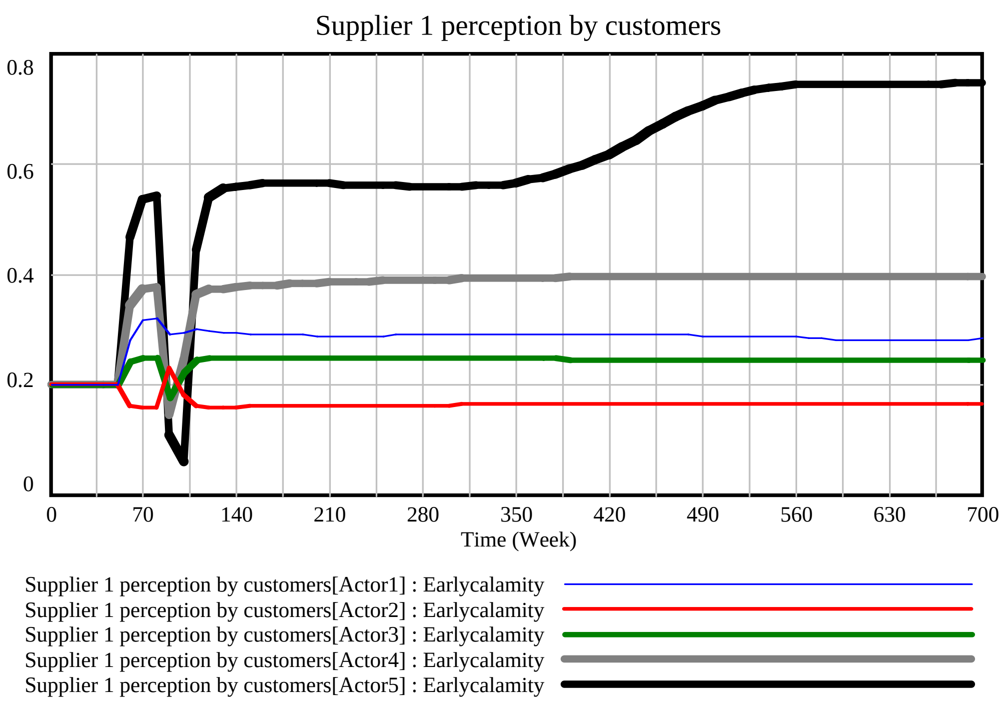

Figure 3: Evolution of preferences of Customers for Supplier 1 after a calamity in Year 1

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).