Emergent Supply Networks: System Dynamics Simulation of Adaptive Supply Agents

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Abstract

Supply chain networks of independent firms collaborating to serve a final market are becoming a normal business phenomenon. Yet at present it is not clear if and how such networks can achieve stability. Nor is it obvious what successful managerial guidelines might be for individual companies operating in such networks regarding collaboration with the other firms involved. This exploratory study investigates these questions using a generic simulation model of 100 actors distributed over three supply echelons. The model was developed in a system dynamics simulation environment using design principles from agent-based modeling. In this model, each actor holds mental models of the performance of the other actors he is interacting with. Preferences for doing business with these other agents are driven by this performance. Agents differ in the degree in which they value long-term relationships over short-term performance.

Model analysis shows that stability in this complex network emerges spontaneously as relative preferences become fixed over time. This lock-in occurs fairly early in the simulation during a period of considerable stress in the various supply chain echelons. Overall, those agents that base their relative preferences primarily on the short-term performance of their counterparts fare somewhat better than agents focussing on the nature of their long-term relationships.

A real-world example of a supply network exhibiting characteristics such as the ones observed in the model is presented. Methodological considerations, model limitations and tentative managerial guidelines are discussed.

1. Introduction

In many of today's turbulent business environments one can witness the emergence of collaborative webs of independent companies. This is also the case in the manufacturing sector, where these webs take the shape of networks of interdependent supply agents []1-7. Often, these networks are very successful, or at least as successful as their vertically integrated counterparts. Theoretically, this causes an anomaly. We know from transaction cost [8,9] that vertically integrated firms will in general be able to achieve lower internal transaction cost through better exchange of information, accelerated learning, greater ease of doing business and the like. But if coordination between these independent supply agents takes place via the ever-changing marketplace, then how can these networks achieve the stability over time that is required for such learning and accommodation? And what kind of policies should management of individual firms operating in these networks have regarding collaboration? Should they still be purely market-driven or put priority on the business interests of their network partners?

This study attempts to find exploratory answers to these questions by simulating a considerable number of such supply networks all interacting with each other. Its theoretical backgrounds are diverse and are discussed in the next section. Section 3 describes the model that was used for this study, Section 4 presents the main findings from model analysis. To strengthen the external validity of this study's findings, an empirical example is presented of a supply network in the high-tech electronics industry that exhibits many of the characteristics found in the behavior of the simulation model. This case is presented in Section 5. Reflections of methodological, theoretical and managerial nature are discussed in Section 6. The main points from this article are restated in Section 7.

2. Theoretical backgrounds

2.1. Decentralized Supply Chain Networks

The advent of the network economy [1] is triggering profound changes in the scope and impact of supply chain management. In the network economy, the vertically integrated business firm may become the exception and ever changing networks of organizations the rule [3,7,10. For many decades, the relevant perspective to maintain in managing a business has been that of the *individual* firm. This has also been the case in supply chain management (c.f. [11]). But recently, the attention in supply chain management has shifted towards inter-firm networks, where the relevant perspective in thinking about supply chain management is at the level of a *network of independent actors* (c.f. [4]). At present, there is considerable unclarity about how these interorganizational networks should be coordinated.

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2.2. Modeling Decentralized Supply Chains in Mainstream OR/MS

For a long time, the field of operations research/management science (OR/MS) has considered decentralized supply chains as an undesirable real-world aberration, rather than a successful business model. This is because mathematical analysis will show that such supply chains, where the constituent actors will strive to optimize their local performance, will have a performance which is sub-optimal to, or at best no better than, an integrated supply chain that is managed from one central position (c.f. [12,13]).

However, recently several articles are appearing in leading journals that investigate optimal policies for management of decentralized supply chains, perhaps partly because of the success of such chains in the real world (e.g. 6,14-17]).

2.3. System Dynamics Supply Chain Modeling

One promising method to investigate interorganizational supply chains through formal modeling is system dynamics. System dynamics can take credit for being the first branch of mathematical research that has investigated management policies for decentralized supply chains. Forrester's *Industrial Dynamics* from 1961 [18] and the famous ''Beer Game'' [19] that was developed on the basis of this work have for decades been dominant in our understanding of amplification effects in supply chains. Meadows's work on the ''hog cycle'' has extended these insights into the business cycle at large [20]. Additions to this body of knowledge have continued [22,23], but the main thrust of this research has been taken over by OM and Management Science researchers such as Hau Lee et al. and their analysis of the so-called ''Bullwhip effect'' ([6,21].

Methodologically, system dynamics has always placed a strong emphasis on the notion of counter-intuitive behavior of complex dynamics systems. That is, due to the intricate interplay between many interrelated factors and the non-linearity of their relationships, the dynamic behavior of complex systems is becomes practically very difficult to predict from a description of their static structure. Hence, simulation modeling and analysis is essential for robust policy design [18,24].

2.4. Agent-Based Modeling

Agent-based modeling is a simulation methodology that employs an implicit world-view [25] that is very close to the perspective of a network of interdependent actors. In agent-based modeling, large numbers of actors are simulated that adapt their behavior in response to changes in their environment. Often, the basic assumptions about this behavior are relatively straightforward. However, as Axelrod, one of the leaders in this field, points out: "Although the assumptions may be simple, the consequences may not at all be obvious. The large-scale effects of locally interacting agents are called 'emergent properties' of the system. Emergent properties are often surprising because it can be hard to anticipate the full consequences of even simple forms of interaction." ([26], p.4).

Agent-based modeling is one of the preferred methods of analysis for complexity research, where complex adaptive systems are being investigated. According to one author, a complex adaptive system is a system "…in which complex behavior of the system as a whole emerges from the interaction of large numbers of simple components, and in which the system is able to adapt - that is, to automatically improve its performance (according to some measure) over time in response to what has been encountered previously" [27, p.1]. Complex systems are adaptive in that they actively seek to make the best out of whatever happens. In being adaptive, complex systems show evolutionary behavior.

In this area of complexity science, insight has been gained on the mechanics of complex adaptive systems. Anderson [28] summarizes the key elements of complex adaptive systems as made out of agents with internal schemata, as self-organizing networks sustained by importing energy, as displaying co-evolution to the edge of chaos and as showing recombination and system evolution effects.

Holland [29] has described three major components of the agents in complex adaptive systems: (1) a performance system, (2) credit assignment and (3) rule discovery.

1. *A performance system* denotes the capabilities of agents at a point in time without attention for change by adaptation in order for agents to react (i.e. the reaction ability).

2. *Credit assignment* denotes the usage of failure or success to assign credit to parts of the performance system in order for agents to adapt (i.e. the adaptation ability).

3. *Rule discovery* denotes the changes made to the capabilities of agents replacing low credit parts of the performance system with new options in order for agents to evolve (i.e. the ability to evolve).

This framework can be viewed as a hierarchy, where each component adds a level of sophistication to and hence possibilities for emergent behavior in complex adaptive systems.

Specialized languages are available for agent-based modeling such as Starlogo [30], ECHO [31] and SWARM [32]. Nevertheless, several of the leading researchers in this field use general-purpose languages such as C or PASCAL (c.f. [26]) because of their personal familiarity with them, the experimental nature of the specialized packages and the inherent flexibility of general-purpose simulation languages. In the present research, a powerful system dynamics simulation package was used [33]. This choice was made partly because of the first two reasons mentioned above. However, most important was the fact that the supply agents to be represented were fairly complex in their ordering and production behavior and well-tested and documented generic simulation models of such supply agents are system dynamics textbook theory (e.g. 34, 24]).

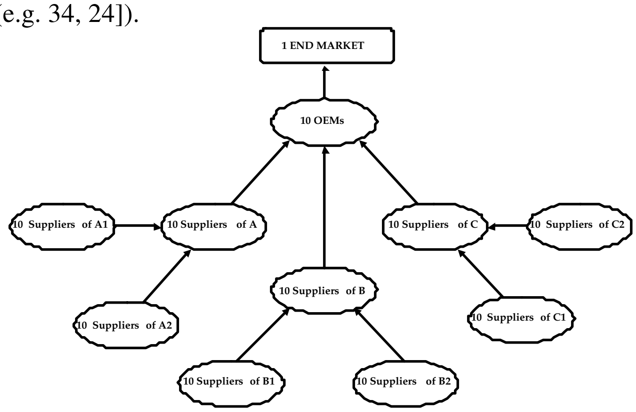


Figure 1: Structure of Supply Bill of Material and Market Segmentation for the Model

3. The Model

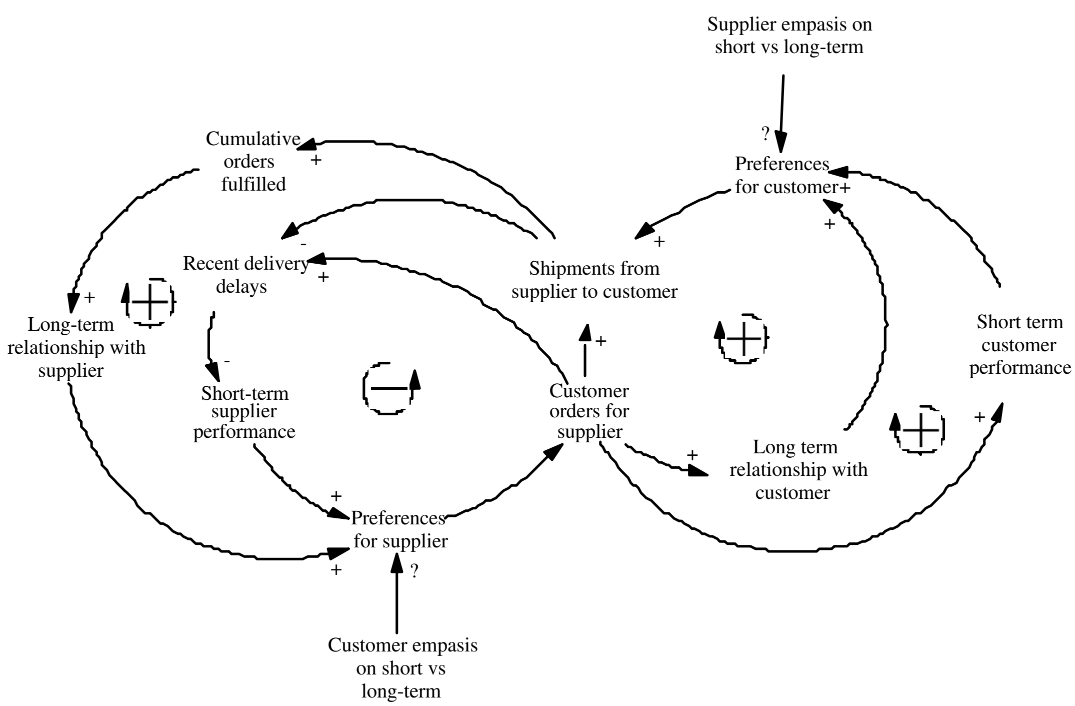
The simulation model that was developed for the research reported here is a generic model of multiple convergent supply networks, all delivering the same kind of end product. The Supply Bill of Material (BoM) of this product is as follows, as can be seen from Figure 1. One subassembly of each type A, B and C is assembled into the final product. A is assembled from component types A1 and A2, B from components types B1 and B2, C from C1 and C2.

These product types are produced by hundred independent agents, or Actors as they are called in the model. There are ten original equipment manufacturers (OEMs) selling the final product, three times ten 1st tier manufacturers of A, B and C, respectively and six times ten 2nd tier manufacturers who deliver components A1, A2, B1, B2, C1 and C2. The final actor is the end market for these products.

Each actor can receive materials from every actor from the tier below it. In this way, ten markets are created for each of the (intermediate) products identified. Needless to say, the potential number of resulting supply networks is huge: each of 10 ten OEMs can receive its materials from 1000 (10 A'sx10 B'sx10 C's) combinations of its 1st tier suppliers. Each of these 1st tiers can receive goods from 100 combinations of its 20 2nd tier suppliers.

Nevertheless, the internal behavior of each of the actors is straightforward. Each time period every actor decides (1) how much of its final product it wants to ship, (2) how much it will produce the coming period and (3) how much material it needs to order. In order to make these decisions, every actor has a mental model of the expected future market demand (based on exponential smoothing of recent customer orders) and information on current internal levels of final stock, work in progress (WIP), materials inventory and production capacity. Given certain targets of safety stock, the above-mentioned rates can be calculated. This part of the model is highly generic and goes back to classic system dynamics models of supply chains like Forrester [18] and Lyneis [34]. The version used in this research is adapted from a textbook model by John Sterman of MIT [24].

What makes this model complex and suitable for generating new insights is the fact that all these actors



carry mental models of the other actors that they are interacting with, that these models are based upon the past behavior of those actors and that every actor adapts its own behavior on the basis of these mental models. On the basis of these models, actors decide how to allocate shipments to customers and orders to suppliers. Every actor has a mental appraisal of both the long-term and the short-term performance of each of its suppliers (this is for the 1st tier actors upward in the chain) and each of its customers (for the 1st tier actors downward in the chain). Both long-term (LT) and short-term (ST) performance influence the relative preference of each actor for its suppliers and/or customers. *The only thing in which the ten actors in each of the ten market segments differ is the degree in which they emphasize the short-term or the long-term performance of their counterparts in determining their relative preferences for them.* Every group of actors has three actors that emphasize long-term relationships three actors that emphasize short-term relationships and three actors that strike a balance between these two. As is shown in Table 2, this means that the ST actors let their preferences for shipments and orders be determined for 75% by the recent performance of their counterparts and for 25% by their history of doing business with them, i.e. the cumulative orders placed or shipments delivered. The LT actors act just the other way round. For them, long-term relationships with counterparts weigh for 75% and their recent performance only for 25%. Three actors use equal weights for both short-term performance and long-term business relation. The tenth and final actor relies for 100% on short-term performance of his suppliers and/or customers in determining his preference adjustments.

Figure 2 shows a causal loop diagram [24] of how these relative preferences reinforce each other. The more a customer orders with a supplier, the higher the supplier's preference for this customer will become over time, and hence his allocation of shipments to the customer. The more shipments a customer receives, the more he will start to appreciate this supplier. Please bear in mind though that, in periods where the overall level of customer orders is not in line with the production rates, delivery delays will differ from normal lead times.

Although it is not apparent how this will play out at the level of individual actors, this will then affect individual customer preferences and hence future order rates.

Table 1: Value Distribution for Emphasis on Long-Term versus Short-Term Performance

(1.00=Total emphasis on LT-relation, 0.00=total emphasis on ST-performance)

Actor	Supplier	Customer
1	0.75	0.75
2	0.50	0.75
3	0.25	0.75
4	0.75	0.50
5	0.50	0.50
6	0.25	0.50
7	0.75	0.25
8	0.50	0.25
9	0.25	0.25
10	0.00	0.00

4. Model Analysis

The model is simulated for nine years or 450 weeks of network development, in which three three-year business cycles for the final product are completed. When we investigate the model's output superficially, we notice the infamous Bullwhip effect, as shown in Figure 3 for the final product, demand for A and for A1. Final demand for the OEMs already contains 40% exogenous demand fluctuation. But fluctuations in demand and hence in production rates and inventory levels are much greater for the 2nd tier-suppliers than they are for the 1st tier suppliers, and their production and inventory levels fluctuate again more than the 40% amplitude of the 3-year business cycle that the OEMs are confronted with. But then this was only to be expected of a multi-echelon supply chain model (See also [18,24]).

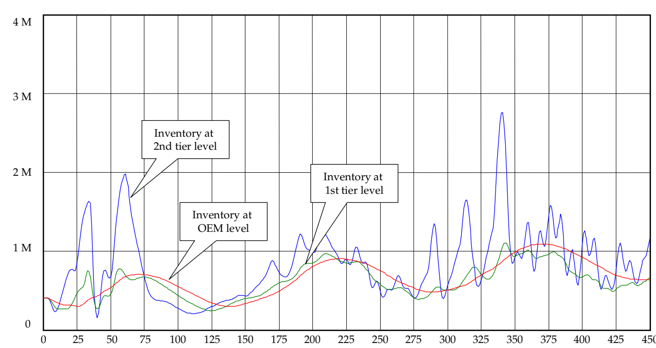


Figure 3: Amplification of Customer Demand in the Three-Echelon Supply Chain

Further in-depth analysis of the model behavior identifies two key characteristics of this model's behavior that are highly relevant to the research question for this article. Firstly, that despite the independent nature of the agents, *soon very stable supply networks emerge,* i.e. networks in which relative preferences for specific suppliers and customers remain fairly constant. And secondly, that an *orientation that is tilted towards recent performance does result just as well in long-term stable relationships* with these actors. Moreover, the actors that are oriented towards short-term performance of others outperform the actors with a long-term focus as well as those with a mixed long-term and short-term orientation. The remainder of this section discusses these two main findings more in detail.

1.1. Stable Networks Emerge

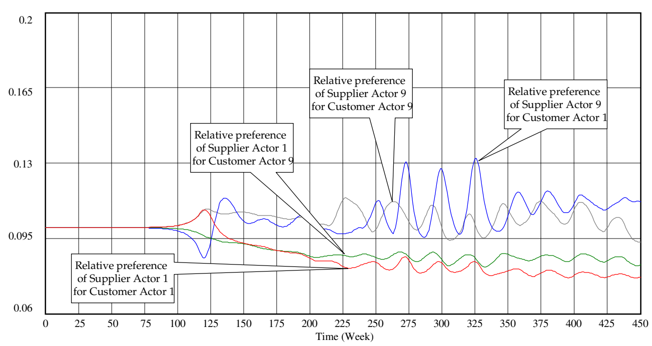


Figure 4: Development of Selected Preferences over Time

4.1.1 Preferences are Formed During Period of Severe Stress on the Supply Network

Initially, all actors start with equal preferences for each other. This means that, as long as there are no differences in short-term performance such as lead time or order volume, preferences will continue to be indifferent for all actors. However, during the slump of the first business cycle in weeks 100-125, as customer demand becomes less and less, preferences start to differ amongst the 1st tier suppliers. Those actors that are focused more on short-term performance will start supplying differently from those actors that remain focused on their long-term relationships. This is visualized in Figure 4 for selected preferences of customers for and suppliers of subassembly A: Actor 1 is short-term oriented, Actor 9 has a long-term bias.

It is too easy to say that the ST-customers will become more attracted to the ST-suppliers and that the LT-suppliers will remain initially remain loyal to the LT-customers and vice versa. This is certainly what happens initially, but then far more complex interactions start to occur and the result is somewhat different for every market. For 2nd tier suppliers this moment of differentiation starts sooner, already during the first peak in Year 2 of the simulation. This is understandable, since the Bullwhip effect is creating considerable stress on this echelon as early as that. In all instances, it is under severe stress that preferences are first differentiated in this supply network.

4.1.2 Relative Preferences Become Firmly Fixed Over Time

It is important to note that, *after the 125 week mark, preferences continue to become more outspoken but their relative ranking stays mostly fixed for the remaining 7.5 years*. In other words, lock-in [35,36] has occurred. This is true for both suppliers and customers. Customers on the whole have less volatile preferences than suppliers do and actors with a long-term orientation are understandably less likely to change their preferences than those with a short-term orientation, but overall the relative rankings remain unchanged.

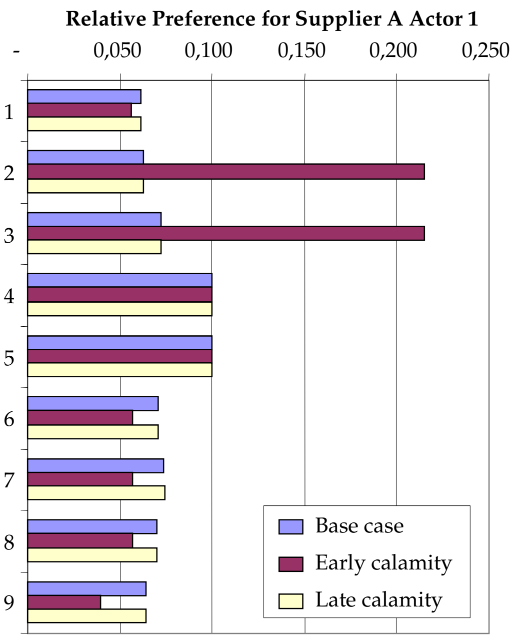


Figure 5: Changes in Relative Preferences after an Early and a Late Supplier Calamity

This lock-in becomes all the more apparent from a simple experiment. Suppose that, through some kind of calamity, one 1st tier supplier loses all its stock and WIP in a single week. If this happens in the first year of the simulation, then the long-term customer preferences for that supplier are very different from the base case. But if the same calamity happens half-way the simulation, after five years, then customer preferences for this supplier remain virtually unchanged. This is visualized in Figure 5, which shows the relative preferences after nine years of the 10 OEMs for Supplier 1 of material A in the base case, after a major calamity at week 50 and after a major calamity in week 250, respectively. Please note that there are hardly any differences between preferences in the base case and the situation with a calamity as late as week 250. But if we look at the scores for the early calamity, we see that only the preferences of customers 4 and 5 have remained stable: Our unfortunate supplier has become slightly less popular with customers 1 and 6 to 10, but considerably more popular with OEMs 2 and 3. Ironically, the net result of this change in preferences due to a total loss of stock and WIP (and hence, the ability to ship) in Year 1 leads to a net increase in Actor 1's cumulative shipments of 21% after nine years, compared to the base case. This is because of its strongly increased popularity with customer actors 2 and 3, who are fairly successful in this market segment.

Another interesting phenomenon is that, with a complete reversal of management policy from short-term to long-term and vice versa, the other nine agents simply more or less persist in their old order and shipment allocations and hence preferences remain unchanged throughout. Apparently, a Nash equilibrium [26] has been reached for the other nine agents by this time, in which it is no longer advantageous for any of the players to change their current preferences.

4.1.3 Preferences Are Subject to Path-Dependency Effects

The model described here is fully deterministic. It yields the same results every time it is run. And yet no two market segments display identical behaviors. Overall, although some common modes of behavior can be observed, as we will see below, the market for e.g. A1 is not equal to the markets for A2 or B1. In both echelons, the distribution of preferences is different although the relative distribution of preferences and priorities is the same as are all the initial inventory levels, production rates and the like. Apparently, very small changes in order levels early on are exacerbated over the course of the simulation period. This is again, just like lock-in, a phenomenon typical for complex adaptive systems, which has been nicknamed the ''butterfly-effect'' by some: the idea that the flapping of some butterfly's wings in China can change the weather in the e.g. the Caribbean some weeks later [37]. The somewhat less evocative academic term is path-dependency [35-37].

4.2. Short-Term Orientation Not Considered Harmful

Overall, agents stressing the short-term performance of their business partners in determining their relative preferences for them do better, in terms of cumulative shipments and material secured, than those agents that emphasize the long-term relationship they are having with their partners. Moreover, short-term agents are just as stable network partners as are their LT-counterparts. Actors in the model that operate both as supplier and customer can have a successful short-term orientation in one role even though they are operating from a long- or medium-term perspective in their other role.

4.2.1. Short-Term Agents Are Stable Network Partners

It seems reasonable to state that supply networks need some degree of stability in their constituent links. Through stability over time, transaction costs [8,9] can be lowered because of mutual learning, easier communication and other forms of coevolving [7] or coevolution [38]. Therefore, one would expect that a long-term view were required from the constituent partners of such a network. Equally, one would expect that actors with a short-term orientation would keep shifting preferences in their participation in supply networks. This is not the case.

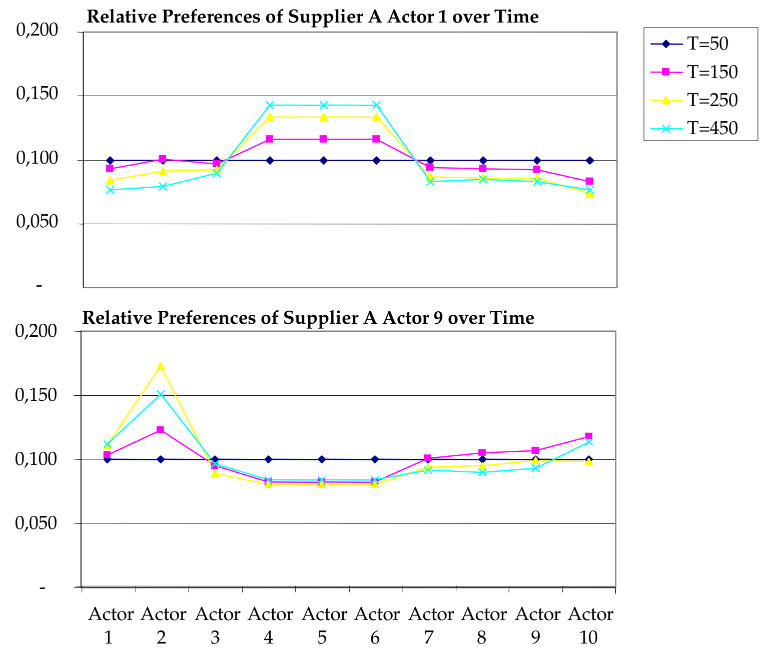


Figure 6: Relative Preferences Stay Fairly Fixed After Lock-in Sets In

Although, in our model, actors with a short-term orientation keep evaluating their preferences and commitments for their business partners, the net result is that the ranking of these preferences remains relatively stable over time. Figure 6 shows the development over time of the relative preferences for two agents from the Supplier A group, Actor 1, with a clear long-term orientation, and Actor 9, with a strong short-term orientation. What the reader will notice is that relative rankings stay fairly stable. In most cases, the absolute differences are increased: preferred customers become more preferred as time goes by, and vice versa. This is not true in particular for Actor 9's preference for Actor 2, which is very high after five years but drops back somewhat after nine years. However, Customer 2 remains the first choice for Actor 9 throughout this period. So, although individual preferences do continue to fluctuate and whilst those fluctuations over time tend to be higher for agents with a short-term orientation, relatively soon relative preferences become more or less locked and, from there on, both ST and LT agents have become long-term partners in a stable network.

4.2.2 On Average, Short-Term Oriented Actors Outperform the Others

If one accepts cumulative shipments as an acceptable proxy for long-term performance for both supplier and customer actors, then we find that short-term oriented actors tend to outperform the actors focused on long-term relations and those that keep a balanced mix. This is especially true for the customer side: here the ST actors ship 8% more than the average level, and the LT-actors 11% below average. From the supplier perspective, the difference is not so significant: +2% versus –2%. Incidentally, Actor 10, the opportunist *pur sang* in this crowd, does best by far as supplier (+10%) and very good as a customer (+7%).

Table 2: Cumulative Shipments for Actors across Market Segments
(Categorized by Emphasis on LT versus ST Performance, in % of Overall Average)

Orientation		*Suppliers*	*Customers*
Long-term	Actors	1,4,7	1,2,3
	Score	98%	89%
Mixed	Actors	2, 5,8	4,5,6
	Score	96%	100%
Short-term	Actors	3,6,9	7,8,9
	Score	102%	108%
Purely short-term	Actors	10	10
	Score	110%	107%

4.2.3 Consistent Behavior as Supplier and Customer Is Not Required for Short-Term Actors

Thirty actors in this model operate both as suppliers and as customers. These are the 1st tier suppliers of types A, B and C. For these actors, it is interesting to see to what degree consistency in behavior in both roles is beneficial for performance. What we find here is that consistency is not required, neither from the supplier nor from the customer perspective.

From the supplier perspective, Actors 3, 6 and 9 have a ST orientation. Of these, Actor 3 is LT-oriented as customer, Actor 9 ST-oriented and Actor 6 holds the middle. There are no clear differences between their performance. If anything, the consistent behavior of Actor 9 is not rewarded in his supply role, since he scores 1% below average, whereas the inconsistently performing Actor 3 scores +1%.

From the customer perspective we look at Actors 7-9. Of these, the consistently behaving customer (Actor 9) scores –2% versus the average whereas the two other ST-customers both score +1%. Although these differences are not big enough to suggest that inconsistent behavior is significantly rewarded, they are even less indicative of a positive correlation between consistent behavior in both roles and successful performance.

Table 3: Consistent behavior as Supplier and Customer is not Beneficial
(Cumulative shipments for short-term 1st tier actors in their two roles as % of average)

Orientation		*Suppliers*	*Customers*
Consistent (ST and ST)	ST-Actor	Actor 9	Actor 9
	Score	99%	98%
Somewhat inconsistent (ST and MT)	ST-Actor	Actor 6	Actor 8
	Score	101%	101%
Inconsistent (ST and LT)	ST-Actor	Actor 3	Actor 7
	Score	100%	101%

5. A Real-World Example

This research was originally inspired by the real-world example of the very successful supply network ASML, a manufacturer of state-of-the art lithographic equipment, i.e. the machines that manufacture wafers of integrated circuits (ICs). ASML has its headquarters located near Eindhoven in The Netherlands. The information presented in this section is based on publicly available material and interviews with company executives responsible for developing ASML's supply network [38,39]. Like the OEMs in our simulated network, ASML has always produced only some 10% of its end product, so-called wafer steppers or wafer scanners, internally. This has been so from the onset, and is a remarkable difference with its main competitors, Canon and Nikon, who are both assumed to be highly vertically integrated.

The bulk of production is outsourced to broadly speaking three types of suppliers: producers of optical equipment (lasers, lenses), of mechanical and of electronic equipment. The company has some sixty key 1st tier suppliers, but its entire supply network is easily more than a tenfold of that. With the bulk of its key suppliers, ASML accounts for less than 25% of these companies' revenue. Nevertheless, there are some companies or business units of larger companies where the dependency on ASML orders is considerably higher.

As with most high-tech companies, the managerial attitude with ASML has been relatively opportunistic, also in its behaviour towards its supplier base. Nevertheless, there has been a considerable emphasis on developing long-term relationships with key suppliers. As a result, several if not most of ASML's key suppliers today are the same ones that the company started off with over fifteen years ago, which corresponds with the simulation model.

Mutual trust and transparency play an important part in this management policy. This trust has been severely tested in the past due to the steep ramp-ups and ramp-downs that characterize the lithography industry, where year-over-year changes of over 40% are not uncommon (as compared to 37% for the U.S. machine tool industry [6]). Suppliers are surprised by sudden decreases in ASML's orders when the IC business cycle turns downward and face considerable supply chain difficulties as a result. As a result, some suppliers are reluctant to trust a steep increase in orders as the business cycle turns up again. Despite ASML's emphasis on long-term relationships with suppliers, it is with these skeptical suppliers that the company's level of business decreases over time. This is again similar to what we found in our simulation model, where preferences changed most rapidly in periods of considerable stress on the supply network. Also, the three-year business cycle and long-term growth rate of around 20% fit with the incoming customer order rate in the simulation model for this study.

6. Discussion

6.1. Methodological Considerations

The research reported here is clearly exploratory in nature. Most research on decentralized co-ordination between multiple agents in general, and in supply chain management in particular, is very recent and preliminary. This obviously also holds for our research. Exploratory research remains an unusual research approach in the field of production and operations management. In two literature surveys from the early nineties, theory-testing research designs were found in 85% of all articles published [40,42]. As such, theory-building remains a step in the research process which has been lamented as sorely missing in production and operations [41,42]. Our research here should make a modest and explorative contribution to theory-building on decentralized supply chain coordination.

One obvious methodological observation to make is that it appears feasible, and even advantageous, to implement agent-based models in a system dynamics environment. Of course the excellent work of Sterman and Wittenberg [43] had given use one instance showing that this was possible, but this study is another early combinations of these two approaches to modeling complex adaptive systems. For the author, the maturity of the Vensim language, and hence its advanced functionality, ease of use and robustness, contrasted starkly to the much more "experimental" nature of the specific agent-based modeling environments he has encountered. Moreover, given the complexity of the behavior of the supply agents involved, and the well-developed body of knowledge on representing supply agents in system dynamics, the author would have been hard-pressed to develop similar functionality in another modeling environment or general-purpose language. It is feedback perspective which is inherent to system dynamics modeling that drives most, if not all, of the decisions and actions of actors in these supply networks.

Another, more fundamental, methodological consideration is that this research design employs simulation to look for new knowledge, to build new theory. This is again unusual. Simulation experiments are normally seen as a suitable research design for theory-*testing* in operations management [40]: for finding out if a theory will work or to what extent it will work if experiments in reality are expensive, time-consuming, dangerous or impossible [25]. And yet, if a simulation is no better than the assumptions built into it, how can it generate new knowledge, new theories? A most eloquent reply to this valid question has been composed by Herbert Simon, who stated some thirty years ago in this context: "even when we have correct premises, it may be very difficult to discover what they imply. All correct reasoning is a grand system of tautologies, but only God can make direct use of that fact. The rest of us must painstakingly and fallibly tease out the consequences of our assumptions." [44 p.19].

6.2. Limitations and Links

There are many obvious limitations to this study. The firms simulated here have no real capacity constraints with considerable delays in building up (c.f. [45]). Also, there are no increases in product functionality or fluctuations in production and product quality as might be expected in industries that are growing some twenty percent per year. Nor is asset specificity [9,36] represented explicitly: all suppliers in a market segment are manufacturing the same products for all customers from the start and continue to be able to do so equally well, regardless of their level of involvement in its production. There are no switching costs [8,36]]in moving from one supplier or customer to another. Nor do firms perish or are they taken over by others, eliminating possibilities for vertical integration, a normal business strategy in many industries (c.f. [46]). Finally, from an agent-based modeling perspective, the agents in this model do not breed, nor is there rule discovery (c.f. [29,47]). One could say that there is some form of machine learning taking place, in the sense that actors keep adjusting the mental models they hold of their opponents (credit assignment, in the terminology of Holland [29]), but this learning algorithm is certainly not overly sophisticated (c.f. [47]).

Despite these limitations, it must also be noted that the main findings from this research appear to fit well with progress made in other studies performed from a perspective of agent-based modeling and complexity theory. Our first main observation, i.e. that preferences become locked early on, is consistent with findings from complexity theory and economics regarding lock-in and path dependence (e.g. [24,26,35,36]. And our second main observation, i.e. that an orientation on short-term behavior of your partners tends to be beneficial over the long term is mirrored in game-theoretical research such as the ground-breaking work done by Axelrod on the iterated prisoner's dilemma problem [48]. The strongest algorithm emerging from that research, TIT FOR TAT, also evaluated the performance of other agents solely on their recent behavior and adjusted its own recommended course of action as well. Nevertheless, this soon led to a population of agents all collaborating continuously and successfully with each other [48].

6.3. Managerial Implications

The rules for how to operate in networks of interdependent companies are new and mostly unwritten [10]. This study has attempted to generate some tentative first attempts at rules for companies operating in such environments, to allow for rigorous testing and further refinement.

One such possible managerial guideline is that one should not be afraid to insist on consistently good performance with suppliers, even when one is already having a close relationship with them for a long time. Recommendations such as these are also heard from the field of business strategy, such as Eisenhardt's and Galunic's study into co-evolvement [7]. Here these researchers found that, in looking for genuine synergies between business units, business unit managers should be rewarded for their individual, short-term performance, not for collaboration for its own sake.

Another finding from Eisenhardt and Galunic [7] is not replicated in the present study. This is their observation that managers routinely keep changing their web of collaborative links. In this model, such continuous changes in network set-up were not found. This may be at least partly due to the above-mentioned limitations inherent tot the design of the simulation model used. Alternatively, it may also be a matter of aggregation level: Eisenhardt and Galunic may be talking about different links but with the same business partners. Nevertheless, one recommendation emerging from this study might be that, when looking for new opportunities and resources, it may be beneficial to start looking within one's present customer and supplier base.

7. Conclusions

This article has described an exploratory study of emerging decentralized supply networks. A simulation model of one hundred firms operating in a three-echelon convergent supply chain was developed in a system dynamics simulation language using concepts from agent-based modeling. Apart from their location in this network, agents only differed in the degree in which they base their relative preferences for customers and suppliers either primarily on their short-term performance towards the agent in question, or mainly upon the intensity of long-term relationships, or on both.

The main findings from this study are twofold. Firstly, that stable supply networks emerge spontaneously as relative preferences for specific customers and suppliers start diverging. This divergence occurs when the supply chain becomes strained for the first time, either by a steep ramp-up of production or a rapid fall in orders. After this happens, the relative ranking of these preferences does no longer change.

A second main finding from this research is that, in general, it appears advantageous to shift preferences for customers and suppliers based primarily on their short-term performance towards the firm in question, as opposed to mainly based upon the intensity of long-term relationships. Firms that allocate priorities based on short-term performance do better than their more long-term oriented counterparts. This is especially true for opportunistic customers, less so for supplier behavior.

It appears that emergent supply networks, however fast the company they are keeping, are here to stay. This article has attempted to illustrate that the same can probably be said for the happy marriage between agent-based modeling and system dynamics as a means for understanding how such networks should best be coordinated.

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