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Abstract

In long-term, recurring contractual relationships, which are common in the B2B-area, reputation and trust play an outstanding role. The impact of reputation and price-based assessment of suppliers on the material flow in the supply chain will be investigated in this analysis. Positive reputation proves to be a key factor to reach a market dominating position. We observed in our simulation, that the assessment of suppliers towards a reputation-based choice has a positive effect on supply chain stabilitiy. In the worst case, a strong reputation-based choice leads to the formation of monopolies. The Bullwip-Effect, that could be observed as a second phenomenon in our simulation setting, represents a countertendency to the reputation-based monopoly effect. This countereffect is observed to be even stronger for members of tiers with a high fluctuation of order rates.

Keywords

Supply Chain Management, reputation, multi-agent-systems

1 Introduction

1.1 The Impact of Reputation on Supply Chains

Understanding inter-firm relationships in supply chains is becoming more important in modern economic theory. Intra-firm focussed enterprise resource planning systems are well known, but they lack gazing at the supply chain as a whole.

Understanding and controlling the dynamics of supply chain processes is crucial to a company's success (Lambert, Cooper, Pagh 1998). Therefore, research in supply chain management has become a broad field in recent years. In long-term and revolving relationships, as often observed in B2B-relations, reputation and trust gain fundamental importance. The impact of reputation and trust on supply chains will be investigated in this study by using an agent-based simulation.

Supply chains or supply webs consist of relationships between several legal independent firms, appearing in one direction as consumers buying commodities and selecting suppliers, and in the other direction as suppliers by themselves selling their finished products to other firms or customers.

Products and services are sold in one direction, directly opposed by a financial stream of payments. The supply web may vary in depth by the number of tiers as well as in broadness by the number of competing firms one tier consists of.

Decentralized decision behavior is a characteristic attribute of supply chains. Decision competence in firms is centralised, with the management serving as head of the system. In supply chains, firms are interacting, trading on markets or establishing contractual relationships with partners, no central instance is coordinating and optimizing the whole supply chain.

Supply chain management operates on strategical, tactical and operational levels. On the strategical level, long-term plans on a high level of abstraction are made, while the tactical deals with the implementation of these plans. Concrete realisation is done on the operational level (Fox, Chionglo, Barbuceanu 1993). This simulation focusses on the tactical and operational levels.

Knowledge of relevant data in the supply chain is generally decentralized and not available to all members. In order to model decentralized decision competence as well as decentralized distibuted knowledge, we used Agent Based Computational Economics (ACE) as our simulation paradigm, especially multi-agent simulations (Tesfatsion 2000).

Firms in the supply chain are represented by economic agents, they only have limited knowledge of the processes in the supply chain and their decisions are based on this limited knowledge. The behaviour of the system not only results as the sum of the individual decisions, the supply chain as a whole shows emerging behaviour (Goldstein 1999).

The simulated agents buy a homogeneous, arbitrary and not further specified good from their suppliers, process it, taking a specified production time, and afterwards sell the transfomed convenience product to their customers. The price for the convenience good is set by the agent, based on information about past demand. In the assessment of a supplier, the agent takes two factors into account, the price of the raw material and the individual reputation, containing information about the reliability in past transactions with this supplier.

Trust reduces the complexity of the decision process because the likelihood of a failed order can be estimated with lower variance and the quality of a product need not be tested immediately (Marsh 1992). Price-focused decisions get less important and the trust of a supplier becomes the key factor. Reputation reflects the past experiences with a certain supplier. A number of positive transactions with a certain supplier increase his reputation, while some failed transactions significantly reduce his reputation.

1.2 The simulation model

Every simulated agent ranks his suppliers by their reputation and their claimed price. With every transaction adequately completed, the supplier's reputation is improved and the likelihood of a new contract with this supplier rises. On the other hand, if an order fails, the reputation of the supplier goes down. Every agent maintains his own list of reputation values for each of his suppliers. Two agents with the same set of suppliers may differ in their assessment of the suppliers as there is no joint rating between agents.
If an agent is in the supplier role, then he can decide whether to accept or deny a specified request by a customer. If the agent believes, that he will not be able to satisfy his customer's needs, then he will reject the request and no order will be generated. Every agent generates a safety stock to buffer unexpected variation in the demand of the succeeding tier. The amount of goods placed in this safety stock is set by the agents themselves, based on information about past demand.
The last customer, the supply web's dip, is triggered exogenous to set a specified demand quantity. Various temporal paths for this exogenous demand can be chosen before starting the simulation. One may chose a constant demand quantity, a demand following a random walk path as introduced by Hall in an extended version of the permanent income theory (Hall 1978), a sinusoidal path to represent economic cycles or a constant demand quantity with shocks at regular intervals.
The simulation itself is implemented using the programming language Java.

1.3 Related research

Due to the specific structure of the underlying problem, supply chain management is an ideal domain for the application of multi-agent systems. Therefore, a lot of research has been contributed to this area and there already exist several agent-based simulations (Stockheim & Wendt 2002). Focussing on multi-agent-simulations addressing the supply chain as a whole, the following approaches should be mentioned:

- Swaminathan, Smith, Sadeh (1998) developed an agent-based simulation platform to enable others to implement own agents on top of this platform. The system is intended to support the development of decision support systems for specific supply chain questions.
- Fox and Barbuceneau (1993) deal with coordination issues on the tactical and operational level, introducing autonomous agents and coordinating their activities by using cooperation protocols.
- Shen and Norrie (1998) join several systems for planning and controlling production processes in an open, distributed environment, simulating inter-firm cooperations.
- Kalakota, Stallaert, Whinston (1996) developed a real-time information system to control supply chain activities by using a mathematical model to represent the chain.
- Eymann and Padovan (2001) use genetic algorithms implemented in their agents to vary their behaviour. They analyze decentralized coordination in supply chains. Their agents take into consideration information about the reputation of a potential transaction partner and use this to choose the appropriate partner.

The agents implemented in our simulation ought to be classified as reactive agents. They possess sensors to observe their environment and track parameters like price or demand-quantities. They have internal knowledge about the behaviour of their environment and track past values of the interesting parameters. By analysing their sensorial input and combining this information with internal knowledge and defined rules, they deduce their actions (Woolridge 2000). Although decision rules are quite simple, a flexible and complex supply web system is built.

2 Supply Chain Network Simulation

The following section describes the dynamic behaviour of the simulation and explains the core processes performed by the simulated agents.

2.1 The processes of a simulated period

Simulation time is discrete and in every simulated period a fixed number of processes is executed for all agents and processed step by step (see figure 1).

At the beginning of every simulated period, all outstanding orders are checked as to whether they can be fulfilled or not. If the date agreed for delivery of a certain order has expired, the order is canceled, supplier and customer are informed and the customer updates the reputation value of the supplier. The reputation value is updated by multiplying the old reputation value with a specified reward or a specified punishment level, whether the transaction was successful or not. Therefore, at the beginning of a period, there are only those orders outstanding which can possibly be fulfilled.

In the next step, all agents calculate the price of their finished goods. This calculation takes place in certain intervals. It is not performed in every simulated period and the regularity depends on the parameter setting of the agent himself.

All agents then check their safety stocks as to whether the estimated quantity of finished goods for future periods satisfies the safety stock buffer. If there seem to be insufficient goods in a future period, orders are generated to reach the minimum acceptable stock quantity as specified in the safety stock.

At that point all agents calculate the desired level of their safety stock. This calculation also takes place in certain intervals, depending on the parameter setting of the agent.

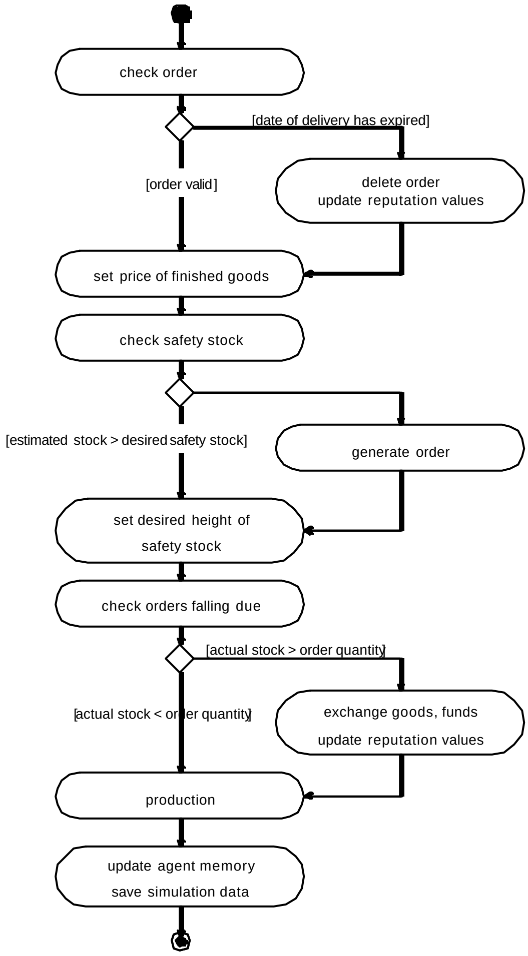

Figure 1:UML-activity diagram of a simulated period

Afterwards, outstanding orders are checked and fulfilled if there is a sufficient amount of finished goods in the agent's stock. Goods and funds are exchanged between supplier and customer.
Finally, production is done and raw material is tranformed one step further to finished goods. The length of the production queue depends on the parameter setting of the agent.

2.2 Setting the price of goods

Setting the price of the finished good is vital for the economic success of the agent. The calculation of the price takes place in certain intervals and it incorporates data of recent simulation periods.
First of all the agent calculates the volume of sales of n recent periods stored in his individual memory. He compares the cumulated volume of sales of the first n/2 periods with the cumulated volume of sales of the second n/2 periods. If sales have grown, the agent concludes a growing demand and raises the price of his own finished goods. In contrast, if sales have dropped, he concludes that his price is not competitive and therefore needs to be reduced. If there are no sales at all, he significantly reduces his price to regain a competitive position. Finally, if sales are equal in both cases, the agent keeps up the actual price. The value of n is set to 20 in this simulation.

2.3 Assortment of suppliers

Before the agent processes requests or buys raw material, all m suppliers of this agent are assessed. The agents consider two factors to assess their suppliers. On one hand they consider the claimed price, on the other hand, they assign a reputation value to every supplier they know. This reputation value reflects past experiences in transactions with a specified supplier. By considering these two factors, a ranking of suppliers can be calculated by the agent.[1] Depending on the weighting of the two factors, price or reputation have a different impact on the supplier ranking. The individual *supplier ranking value* (SRV) of a supplier i is calculated using the following formula:

(1) $$SRV(i) = w * \frac{\min\{p_i \mid i \in 1,...,m\}}{p_i} + (1-w) * \frac{r_i}{\max\{r_i \mid i \in 1,...,m\}}$$

$SRV(i)$:	Supplier Ranking Value of supplier i.
w :	Weighting of price in relation to reputation, $0 \le w \le 1$
p_i :	Claimed price of supplier i.
r_i :	Reputation value of supplier i.

The formula consists of two components, one reflecting the claimed price, the other reflecting the reputation of the supplier. The price component is calculated as the ratio of the minimal price of all suppliers known by the agent in relation to the claimed price of the supplier to be ranked.

The second component, taking into account the reputation value of the supplier to be ranked, is calculated as the ratio of the individual supplier reputation value in relation to the maximum reputation value of all suppliers known by the agent.

Both components, weighted by w, result in the supplier ranking value of the evaluated supplier. The agent is now able to generate a list of his potential suppliers sorted by the supplier ranking value.

2.4 Setting the safety stock

The agents use the information stored in their individual memory to predict the estimated demand in future periods. In order to be able to tolerate slight fluctuations, they set up a safety stock buffer.

Initially, the agent calculates the mean value of the quantity of goods for all accepted orders in his memory. He adds the mean value of quantity of goods for all declined order requests. This takes care of a slight increase in demand level. If the agent declined a lot of order requests in the past because of insufficient stock, he was consistently understocked and therefore has to increase the safety buffer.

(2) $$stock^s = s * \left(\frac{\sum_{i=1}^{n} q_i^{acc}}{n} + \frac{\sum_{i=1}^{n} q_i^{dec}}{n} + \max\{q_i^{can} \mid i \in 1,...,n\} \right)$$

$stock^s$:	Desired safety stock.
q_i^{acc} :	Quantity of goods for the accepted order i.
q_i^{dec} :	Quantity of goods for the declined order i.

[1] Cp. Padovan et al. (2001) for a similar approach.

q_i^{can} : Quantity of goods for the failed order i.

s : Scaling factor s, s > 0.

To minimize the loss of reputation due to failed orders, the agent adds the maximum quantity of goods for all failed orders in his memory to avoid being short on goods in the future. In this simulation, his memory incorporates information about the last 20 periods.

The scaling factor *s* can be configured individually for every agent. By setting the scaling factor to values lower than one, agents with an aggressive way of calculating the desired stock can be modelled. By setting it to values greater than one, agents accepting high store quantities to avoid reputation loss can be generated. In this simulation, the scaling factor for all agents will be set to one.

2.5 Processing an order

First of all, the customer-agent sends a message to all his suppliers and requests the actual prices for their respective goods. Based on this price vector and the stored reputation vector, the agent can calculate a vector containing the supplier ranking values of all his suppliers.[2] Subsequently, he sorts this vector descending by value and sends an order request to the highest ranked supplier, specifying order quantity and delivery date.

If the supplier confirms the request, an order is generated and both partners, supplier and customer get a reference to the object representing the order. They have agreed upon a contractual relationship. It is up to the supplier to deliver the ordered goods on time and up to the customer to pay upon delivery.

In case there is no supplier able to fulfill the request by the customer, then he will not meet his requirements in this period. He will wait until the next period and retry to fulfill his requirements.

2.6 Checking the stock

Knowing the amount of goods on stock in a certain period, the agent is able to calculate the estimated stock in the next period using the formula:

[2] The calculation of the supplier ranking value is shown in detail in section 2.3.

(3) $$stock_e(t+1) = stock_e(t) + m(t+1) + \sum_{i=0}^{n} q_i^s(t-ptf) - \sum_{i=0}^{n} q_i^c(t+1)$$

$stock_e(t)$:	Estimated quantity of finished goods in period t.
$m(t+x)$:	Raw material, at present in the production queue, completed in x periods.
$q_i^s(t)$:	Quantity of goods for an order i to be fulfilled in period t by a supplier.
$q_i^c(t)$:	Quantity of goods for an order i to be fulfilled in period t by the agent.
ptf :	Time needed to transform raw material into finished goods.

To calculate the estimated quantity of stock for a given future period, one must start with the actual period and iteratively evaluate the estimated quantities for all succeeding periods. Based on information about the estimated stock of a certain period, the agents decides whether to accept or decline an order request.

3 Analysis of the Results

3.1 Analysis setup

Considering comparable products, further factors affect the selection of a supplier, for example product quality, delivery reliability or corporate reputation. In many cases, the customer is not able to check all relevant attributes of a product and reputation of the supplier is playing a major role. It reflects all past experiences with a certain product or supplier which the customer himself or other customers have had.

Initially we investigated the impact of the reputation component upon the formation of stable supply chains out of the broad distributed supply web and the overall performance of the supply chain. We focussed on comparing the market shares of the individual agents and the number of failed orders in ratio to the total number of generated orders.

3.2 Configuration

The simulated supply web consists of four tiers modelling an industrial supply chain with four component suppliers, two manufacturers, four distributors and eight retailers.[3]

This configuration is realistic in that the width of the supply chain often decreases in direction of the manufacturer. Many raw material suppliers deliver their parts to component suppliers, who assemble the parts and sell modules to the original manufacturer. They, in turn, put the modules together and create the finished product. From this point, the supply web broadens for the physical distribution of the finished product, with some distributors and various retailers involved.

The simulated agents are identically configured, differing only in the individual amount of time needed to transfer raw material into finished goods. It takes two periods for first tier agents to transform their raw material to modules, second tier agents, called manufacturers, need four periods. The distributors or third tier agents, take two periods for the regional distribution, and the agents in the fourth tier, the retailers, require at least one period to sell the goods to the last customer.

[3] Due to model reasons, two more agents are created; one acting as the first supplier and always delivering raw material, the other acting as the last customer provided with and given an exogenous demand level.

The exogenous demand level of the last customer always requests delivery with a delivery date lagged by five periods. Demand follows a symmetrical Random-Walk-Path with a stepping of one unit and starts at a level of 40 units.

3.3 Impact of reputation to price weighting

We start the investigation and vary systematically the weighting of reputation to price. A weighting of zero reflects a totally price-based assortment of suppliers, while a weighting of one leads to a pure reputation-based selection.[4]

The reputation value of an agent reflects the past experiences in transactions with a specific agent. Improving reputation is a long-term process, while reputation loss can occur quickly following repeated disappointment (Padovan 2000). If an order is completed successfully, the customer agent increases the individual reputation value of the supplier. A failed order results in a decrease in the reputation value. Every agent holds his own list of reputation values for his potential suppliers. This may result in different reputation values by different agents for the same supplier. Agents of the same tier do not share any information about their reputation ratings.

In this case, agents increase reputaion by 10% once an order is successfully completed, whilst they reduce reputation by 25% for every failed order.

The weighting of the reputation to price ratio is varied in steps by 0.1 starting with 0.0 (a strictly price-based assortment) and increasing up to 1.0 (a strictly reputation-based assortment) of suppliers. We conducted five simulation runs with 1000 simulated periods each for every weighting step.

We observe the market share of each agent after 1000 simulated periods. Market share is calculated as the total amount of goods traded by a specific agent in relation to the total amount of traded goods by the tier the agent pertains to. This value represents the relative quantity of goods traded by the agent and is a good indicator for his economic size and weight.

In figure 2, the weighting of price to reputation has been plotted against the respective relative market share of the largest agent.

To assure comparatibility amongst all tiers, the relative size is shown here. Assuming an equal distribution, a first tier agent should reach a market share of 25% because tier one consists of four agents dividing the total goods transfer among them. This diagram shows the deflection of the largest agent to this expected value. For example, considering a weighting of 0.2, the largest first tier agent is on the average 11.57% larger than expected. The expectation for second tier agents would be 50%, for third tier agents 25% and for fourth tier agents 12.5%. This diagram shows the respective deviations only.

One can notice the tendency to large deviations and therefore dominating agents for large weightings in favour of the reputation component. This effect is most destinct for retailers. As one can see, if choosing a purely reputation based assortment, the largest retailer is on average 68.90% larger than expected.

[4] See paragraph 2.3 for further details of the employed assessment process.

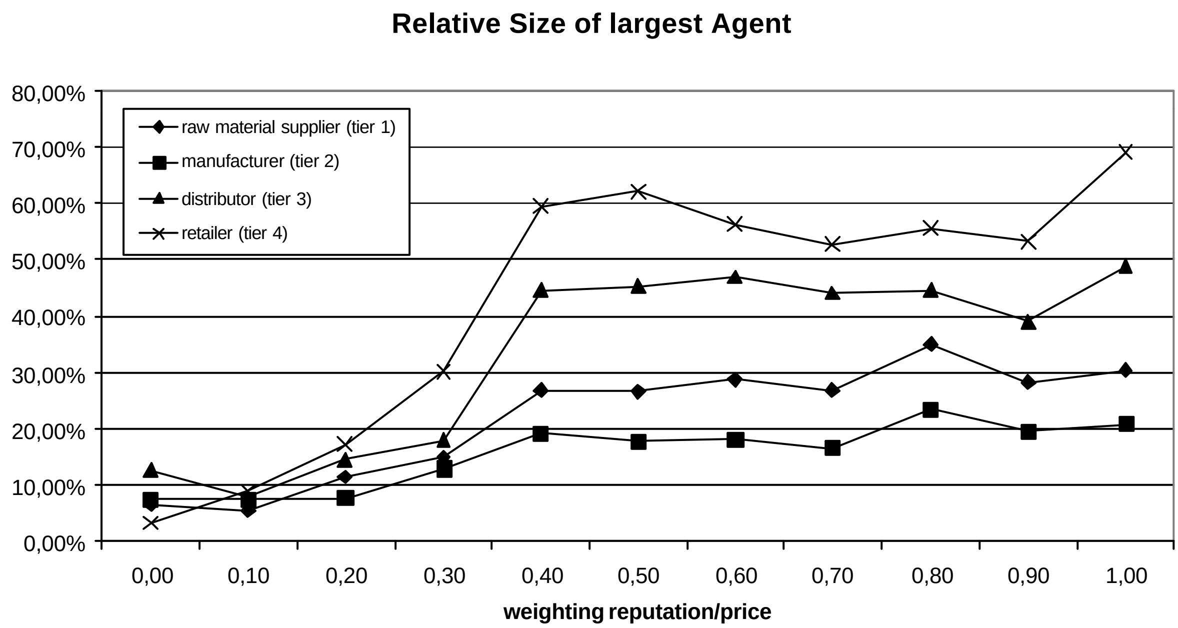

Figure 2: Relative Size of largest Agent

With a weighting towards the reputation component, stable supply chains emerge, carrying the main amount of goods transferred. Dominating monopoly agents appear for every tier in the supply chain, handling a vast amount of goods transferred.

In contrast, if switched to a price-based assortment, market shares are approximately equally distributed. Without any impact of reputation (weighting zero), the respective largest agents of the different tiers are at most 12.75% larger than expected. Agents change their suppliers more frequently, always seeking the lowest price. As soon as an agent claims a higher price than a competitor, he immediately loses all demand, rendering his products uninteresting for customers. For this reason, none of the agents are able to establish a monopoly or even dominant position compared to a competitor.

Considering a higher weighting of the reputation component, an agent will not lose all order requests if claiming a higher price. If his reputation is high enough to offset the higher price, he will continue to attract customers further on and therefore be able to establish a monopoly. A high impact of the reputation component in supplier assortment emphasizes the formation of dominant monopoly agents. This effect is more distinct for those tiers close to the last customer.

It is noticable that even with a total disregard of the price component, agents may establish dominant positions but not total control of their respective market. The larger manufacturer agent of tier two reaches a market share of 70.88% by complete disregard of the price component, leaving 29.12% of the market to the smaller one. The second manufacturer agent is able to provide goods if the larger one isn`t able to accept an order request. Therefore the smaller manufacturer acts as an alternative source for rare products.

We notice this phenomenon for all tiers of the simulated supply web. The smaller agents act as a back-up source for goods, smoothing the goods circulation through the supply web and, therefore, providing a permanent supply.

Considering the performance of the supply web, measured by counting the number of failed orders in relation to the total number of orders, a slightly increasing contingent of failed orders correlates with an increasing importance of the reputation component.

The use of reputation to assess suppliers favors the formation of stable supply chains and dominating monopoly agents, while lacking a distinct impact on the total performance of the supply web.
Assigned to the real world, customers taking brands and reputation into account favor the formation of stable supply chains with dominating monopoly agents. As a regression analysis shows, a purely price-based assortment of suppliers would be favourable because the contingent of failed orders in relation to total orders slightly increases by raising the weighting of the reputation component.

3.4 Impact of punishment level on failed orders

Furthermore, we vary the amount of reputation lost in a failed order and analyse the impact on market shares and performance as we have done in the investigation before. The weighting of the reputation to price ratio was set to 0.5, both components being equally weighted. The loss of reputation was globally set to 10%, 50%, 75%, 90% and 95% of the original value. For this reason, the 10% level denotes the highest punishment because the agent loses 90% of his former reputation. On the 95% level, the agent loses 5% of his former reputation. We performed 15 simulation runs, each conducting 1000 periods, for every respective punishment level.
As noted earlier in the investigation, stable supply chains and dominating monopoly agents emerge for low punishment levels. Again, this effect is more distinct for retailers or distributors than it is for raw material suppliers or manufacturers. The following diagams show the mean values of the market shares of retailers and raw material suppliers sorted by size for the different punishment levels.

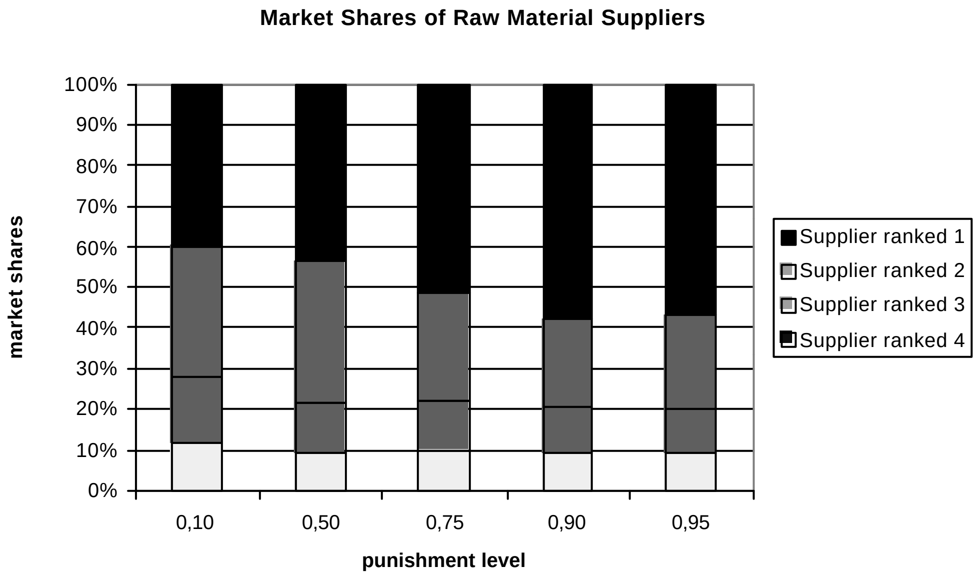

Figure 3: Mean values of market shares of tier 1 suppliers (raw material suppliers)

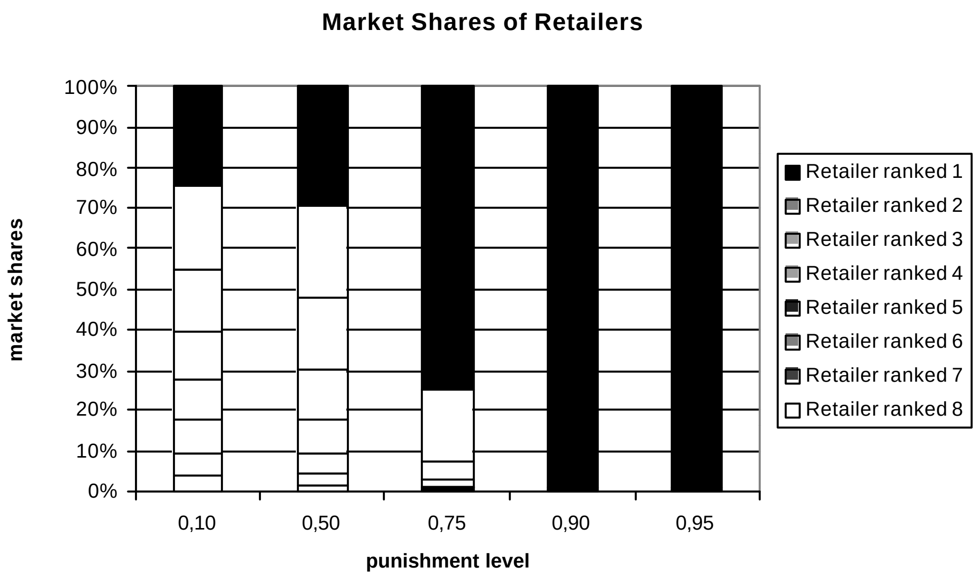

Figure 4: Mean values of market shares of tier 4 suppliers (retailers)

As shown in figure 3 and 4, at the 95% punishment level (the weakest level), the largest retailer occupies nearly 100% of the market. The largest raw material supplier reaches 60% market share on the same punishment level. The monopoly effect is even stronger for weaker punishment levels and for tiers in close contact to the end customer. This effect is due to the lower deviation of order quantities for tiers relatively close to the end customer. Retailers have direct access to the actual demand of the last customer. Since the exogenous demand of the last customer is configured following a symetrical random walk with a stepping of one, demand quantity will vary little between two simulated periods and retailers are mostly able to accept a request for order.

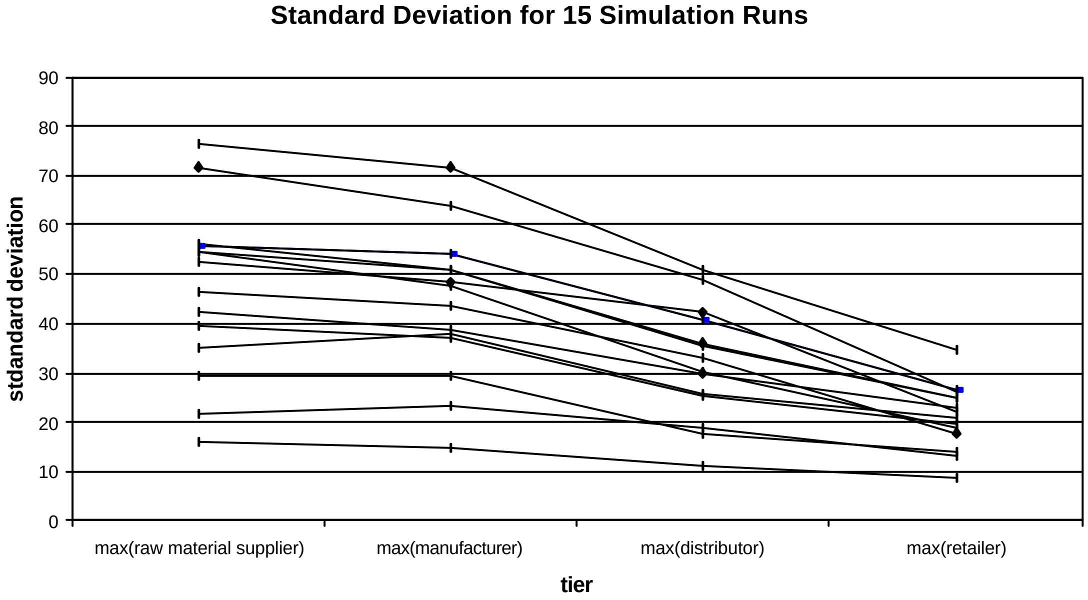

Figure 5: Standard deviation of order quantity for 15 simulation runs

The information about actual demand quantity reaches raw material suppliers indirectly through the order quantity of the manufacturers, who themselves get this information from the distributors and so on.

Therefore, order quantities vary more extremely for raw material suppliers than for retailers. This diagram illustrates the standard deviations of the order quantity for each tier taking the agent with the maximal variance for 15 simulation runs. As one can see, there is a tendency toward higher variation in order quantity for tiers far away from the actual source of demand, the end customer.

This effect, in common literature referred to as the Bullwhip Effect, imposes a countertendency on the reputation effect. Actual demand variation is often buffered by safety stock. Therefore, actual information on the quantity of demand gets irregular and includes great deviation. The favoured raw material supplier is often not able to serve a request for order and his competitors are asked for delivery. Raw material suppliers would have to buffer large amounts of goods to absorb the greater deviation in demand quantity. In contrast, the favoured retailer is practically always able to accept a request for order. On a low punishment level, he stays the favoured agent even if he increases his price. By using a high punishment level, all agents are able to be ranked first at some time and, therefore, market shares are more regularly distributed.

4 Summary

As a result of our simulations, a higher weighthing in favour of the reputation component at the expense of the price component leads to the formation of stable supply chains and dominant monopoly agents. This effect is more distinct for tiers close to the end customer. As a conclusion, the building of positive reputation represents a key factor for a company striving to reach a dominant position and gather a large market share in a supply chain. On the other hand, customers assessing suppliers by evaluating information about brands and reputation favor the formation of stable supply chains with dominating monopoly agents.

For members of tiers far away from information about actual customer demand, there is a countertendency to the reputation effect due to the Bullwhip Effect. The higher deviation of demand quantity in tiers far away from the end customer leads to augmented failure of orders and counteracts the monopoly tendency released by the reputation effect.

The amount of failed orders compared to the total amount of orders is lower if a selection of suppliers is done using price-based decisions rather than reputation-based ones and, therefore, price competition among the suppliers is favoured. This behaviour was already noticed by Majahan/Ryzin, demonstrating in their respective model the correlation between horizontal competition and supply chain efficiency (Mahajan & Ryzin 1999).

In our model, the structure of the supply chain is fixed and predetermined and all agents of a specific tier are equipped with the same resources. The extension of the simulation model towards dynamic supply web configuration will be subject to future research.

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