Impact of Trust on Agent-Based Simulation for Supply Chains

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Abstract. Companies in supply chains have a goal to optimize their productivity, and hence their profits. One way to study the behavior of these chains is to simulate them using a multi-agent approach. In this work, we propose an extension of a model used in the literature, called the *Beer Game*, by adding multiple agents in each of its levels to evaluate both the local and global performance of the suppliers. We use different agent profiles, based either on trust or on price. By enabling clients to ask supplier sugestions from their peers, we measure how these peers' suggestions and lies affect working capital and trust measures for different agent profiles.

1 Introduction

The main goal of every business is profit [6]. In the context of companies interacting in a supply chain (SC), partnerships based on trust can be more profitable than those based on supply and demand mechanisms. This statement is based on the observation that the greater the trust of a consumer in his suppliers, the greater the responsiveness of these, and therefore the greater the gain for SC [8].

Supply chains are defined as the set of organizations, activities, information and resources involved in the movement of a product or service from suppliers to consumers [14]. The interest in studying the management of these chains, supply chain management (SCM), has been increasing in order to obtain competitive advantages for the market through improvements in its processes [3]. Figure 1 [11] illustrates an example of SC.

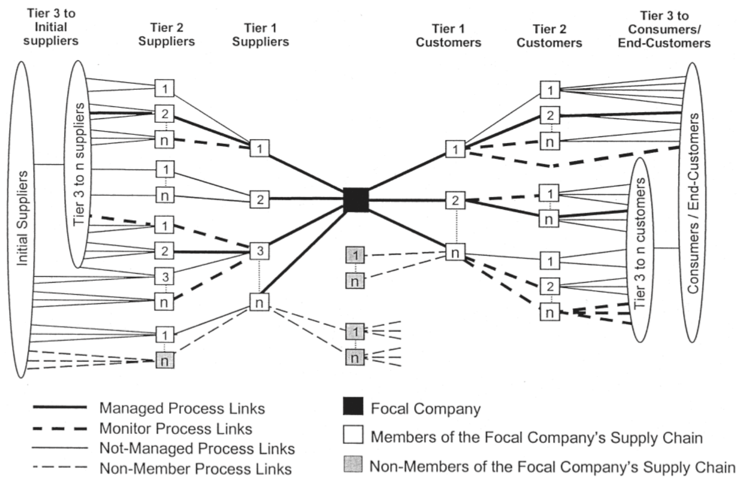

Fig. 1: Example of supply chain [11]

On the other hand, trust may be defined as the predisposition of an agent to place himself in a vulnerable situation in relation to another hoping that this latter provides him with some benefit in return [13]. Since a SC is composed of individual firms collaborating to serve end-users, their effectiveness is highly dependent on trust between network partners [21].

In [19], the authors propose to simulate SCM with the aid of agent-based modeling (ABM), which allows chain performance to be evaluated under different organizational perspectives. In [4], researchers advocate the choice of ABM to simulate SCM because the latter is a physically distributed problem in which agents may consider both their own interests and the one of the entire chain; they also consider simulating SCM a highly complex problem, influenced by the interaction between several variables.

One way to model the behavior of the agents playing different roles in a SC is by using the structure proposed by the *Beer Game* (Section 2), a board game created within SCM and often cited in the literature. In [10], for example, the rules of this game are used in simulation to model the performance of the agents interacting in a SC.

The objective of this work is to analyze the impact of suggestions, lies and trust between entities inserted in the context of an SC modeled by the *Beer Game*, in particular simulating companies with different profiles.

2 *Beer Game*

The *Beer Game* is a board game designed by Forrester [5] to understand SCMs. In this game, teams of 4 players compete with each other; a team represents a supply chain and each team member plays one role, corresponding to four levels of the SC: factory, distributor, wholesaler and retailer. The objective of each team is to manage the stock in face of unknown external demand, trying to minimize the cumulative costs in the sum of the levels of the chain. Each participating team has its own board at its disposal. In the board, each team member has its stock and incoming shipments represented by markers, and orders are annotated on a paper, as shown in Figure 2.

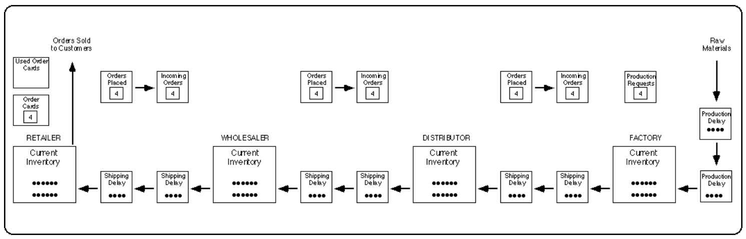

Fig. 2: Board layout for the *Beer Game* [18]

Each player sizes and sends orders to the player who controls the top level, except the factory, which sends orders to its own production line. Each player also receives and must attend orders received from the lower level, except the dealer, who gets their orders from a stack of paper faced down. This stack represents the demand of the final consumer and has the same ordering and values for all teams. Each player withdraws goods from his stock and sends out shipments to meet the orders of the player controlling the lower level. Each player also receives the shipments shipped from the top level and keeps them in its own stock, except the factory, which receives the shipments from its own production line. If a player does not have sufficient goods in its stock to meet the last order received, the player sends a shipment with the remainder of his stock, and the due portion is noted for shipment in the next round, added to the next order to be satisfied.

The game is divided into a fixed number of rounds, each containing a sequence of actions that must be performed simultaneously by all members of all teams. This sequence is described in Algorithm 1.

Algorithm 1 *Beer Game* - Flow

```
1: for all round do
2:     Receive shipment from supplier
3:     Send shipment to client (who will receive it two rounds later)
4:     Record stock on hand or total due
5:     Receive client order
6:     Send order to supplier (who will receive it one round later)
7: end for
```

At the end of the 36th round, the game is closed, and the winning team is determined as being the one that has accumulated, in all its levels and rounds, the lowest score as defined in equation (1):

$$\text{score} = 0.5 * \text{stock on hand} + 1 * \text{total due} \tag{1}$$

Consumer demand is revealed: it is fixed at 4 units per round until the 4th round, and then it is changed to 8 rounds from the 5th round until the end of the game.

3 State of the Art

Several works that addressed the use of trust in SCM are listed in Table 1, where we show the performance indicator that determines supplier choices, agents' policies and the utility function used for evaluating the SC performance. If we analyze Table 1, we may highlight some relevant points:

Table 1: References addressing use of trust in SCM

Reference	**Performance Indicator**	**Agent Policies**	**Utility Function**
(author?) [1]	Volume of shipments received	Heterogeneous	Amount of supplier switches
[16] [16]	Volume received and delivery speed	Homogeneous	Amount of supplier switches
[12] [12]	Price and delivery time	Homogeneous	Cost, punctuality, cycle time
[10] [10]	Ratio between orders and deliveries	Homogeneous	Stock levels fluctuation
[9] [9]	Punctual delivery rate	Homogeneous	Working capital and active firms
[7] [7]	Product quality	Homogeneous	Quality and profit

– In all references, each company of SC corresponds to a simulated agent, but only in [10] agents follow the Beer Game rules;
– In all references, the performance of a supplier is evaluated by the quantity and punctuality of its deliveries;
– Only in [1] heterogeneous decision policies are used in the same simulated SC, with agents that privilege short-term performance of their suppliers, and others that focus on long-term performance;
– Only in [7] agents ask each other for suppliers' suggestions;
– All the papers analyze the impact of agents' actions from the SC's global point of view, but none of them records or compares the profit of each represented company profile.

In our work, we combined some characteristics of these models. Since the Beer Game model is considered a benchmark for this problem, we have also adopted it for our work, like [10]. Like [1], we also enabled heterogeneous decision policies for the agents, since this option is more realistic. Another natural choice is to represent recommendation from peers in our model, like it happens in real cases, as adopted by [7]. Moreover, as we wanted to use a rather simple financial model, we opted to follow the one proposed by [9].

4 Agent-based SCM simulation model

Our research differs from the others by trying to measure the individual performance of agents with different profiles, that may or not use the notion of trust. These agents interact simultaneously in the same SC modeled according to the rules of *Beer Game*.

In our model, we will refer as i to the agent we are focusing on, as j to its supplier and as C to its set of clients.

4.1 Supply chain model

Similarly to [9], the simulated chain is composed of 5 levels: factories, distributors, wholesalers, retailers and final consumers; we considered 20 agents per level. In each round, each agent may order from one supplier at the higher level, as well as fulfill orders made by each of the clients at the lower level.

4.2 Agent model

In this work, we used an agent architecture composed of:

- **Perception**: the agent detects the shipments sent by its supplier and the orders sent by its customers;
- **Reasoning**: the agent reasons and decides which customers to send the shipments to (first deliver to those who it owes more) and dimension the order to the supplier based on the anchoring and adjustment mechanism described in Section 4.3;
- **Action**: the agent sends shipments to his clients and an order to his supplier.

4.3 Ordering by anchoring and adjustment strategy

In [17], the author proposes a model to characterize the way in which companies dimension orders to suppliers in order to control their own stock levels. Such a model is based on the cognitive anchoring and adjustment mechanism (A&A) described in [20], which proposes a heuristic for requests to suppliers so as to:

1. resupply expected inventory losses;
2. reduce the discrepancy between the current and desired stock;
3. maintain a suitable supply line for orders already made but not yet received.

For a more detailed formulation, see [17].

4.4 Working capital model

The proposed financial model is based on the one described in [9]. For each agent, the capital change ΔC after each round is expressed by equation (2):

$$\Delta C = c * O + \sum_i (v - p) * O_i - u * S \tag{2}$$

where (i) c is the unit cost price of the supplier, (ii) v is the unit selling price charged to clients, (iii) p is the unit cost of production, (iv) O is the size of the order made to the supplier, (v) O_i is the size of the order made by each client i, (vi) u is the unit storage cost of the stock, and (vii) S is the stock on hand at the end of the round.
All these values can vary per round, with the cost prices of each agent corresponding to the sales prices set by its supplier. These prices may vary between v^j_{min} and v^j_{max}, calculated by SC level j, as follows:

1. The cost per unit of stock u per round is agreed to be $1;
2. The cost of production p is considered the same for each level of the chain, and parameterized in function of u;
3. For the factory, v^0_{min} equals the cost of production p and v^0_{max} equals v^0_{min} + p;
4. For each level below, v^j_{min} equals v^{j-1}_{max} + p and v^j_{max} equals v^j_{min} + p.

4.5 Supplier trust model

To quantify a client's trust level in a supplier, we used the approach proposed in [9]. At each round, the trust level is given by the historical ratio between the shipments delivered in each round and the corresponding orders made three rounds before. Such measure comprises the sum of the transmission delays of the request from the supplier and the sending of the shipments by the latter to its client, as mentioned in the Section 2. This ratio is expressed by equation (3):

$$Trust_{CFn} = \sum_{1}^{n} C_i / \sum_{-2}^{n-3} P_i \tag{3}$$

where (i) n is the current round, (ii) P_i is the order sent to the supplier in round i, (iii) C_i is the shipment received from the supplier in round i, and (iv) $Trust_{CFn}$ is the trust of client C in supplier in round n.

4.6 Supplier recommendation model

In our model, we consider that an agent may eventually ask his peers for supplier suggestions. With this feature, an agent will possibly have the chance to interact with a better supplier with whom he has never interacted before. We use a parameter ϵ to represent this chance.

4.7 Agent profiles

Each SC level will consist of agents with different profiles. Each of these profiles will be driven by a goal that incurs a combination of decision policies. Two profiles are proposed in this work:

- **Popular:** A popular agent aims to attract as many clients as possible by offering a low price, and to keep them through the most possible punctual delivery of their orders;
- **Greedy:** A greedy agent aims to maximize its profit by buying cheap, selling expensive and reducing expenses.

We consider that a contract between clients and suppliers holds for d rounds (d is a parameter). After this period, clients reassess trust in their suppliers, eventually asking their peers for new supplier suggestions. An eventual supplier change is described in Section and then apply their decision algorithm according to their profile:

- **Popular:** favors high trust suppliers, since delays in order deliveries lead to a stock shortage for the agent in question, which may render deliveries to its clients unfeasible. Algorithm 2 shows this decision for popular agents.
- **Greedy:** favors cheaper suppliers. The algorithm is analogous to Algorithm 2, except that the decision criterion is the cheapest price and the suppliers suggested to them by a peer are the ones that, in the last supply contract with the peer, set a price below half of the interval defined by v_{min} and v_{max} for the supplier's SC level.

Algorithm 2 Supplier choice procedure - Popular Agents

1: With ϵ chance, agent selects a random peer among the ones it relies on, and asks him for supplier suggestions
2: The chosen peer, if a sincere one, informs all good suppliers it has interacted with so far, with trust rate greater than a threshold 0.5
3: The agent then takes the supplier with the highest informed rate and compares with its current supplier. If the first rate is greater than the latter, it switches to the new one. Otherwise, it proceeds to the next step, exploration
4: Agent draws N set of top-level supplier candidates and chooses, among the N drawn, the one with highest trust
5: If the chosen supplier has a higher trust level than the current one, the agent changes from the current one to the chosen one. Otherwise, it keeps the current one

In relation to **stock management**, the behaviors of such profiles are:

- **Popular:** has as desired stock the parameterized safety stock $S*$, in order to prevent against peaks of demand that affect its shipments;
- **Greedy:** does not maintain a security stock ($S* = 0$), in order to reduce the maintenance cost of its stock.

In order to diffentate **prices** set by each profile, offset δ is provided as parameter, so that:

- **Popular:** keeps the price low, in order to attract clients focused on low price. At each round, randomly sets price between v_{min} and $v_{max} - \delta * (v_{max} - v_{min})$, taken from a uniform distribution.
- **Greedy:** keeps the price high, so as to maximize its profit margin. At each round, randomly sets price between $v_{min} + \delta * (v_{max} - v_{min})$ and v_{max}, taken from a uniform distribution.

4.8 Unreliable peers

At the end of a contract, a client records the price and accumulated trust rate for the contracted supplier in order to suggest it to peers. If, for that same contract, the supplier had been reccomended by a peer and it was proven to be a bad one (trust rate lower than 0.5 when asked by popular agent, price in the upper half of the SC level interval when asked by a greedy agent), the peer is marked as unreliable by the client. The peer is not asked for suggestions anymore, and neither answered when he asks for suggestions.

4.9 Liars

In the beginning of each simulation, a fixed share of agents per level on the SC are defined as liars. We represent this fact by a liar rate λ. When asked for suggestions, a liar returns only bad suppliers. To mask its suggestion, the liar transmits each supplier to the peer as if it was a good one, with trust equals (1 - real trust) and price equals (v_{min} + v_{max} - real price).

5 Simulation and results

5.1 Simulation cycle

Algorithm 3, used in this work, consists of an extension of Algorithm 1 of the *Beer Game*, described in Section 2.

Algorithm 3 Simulation - Flow

```
Agents initialize inventory, and order and shipment lines
Clients choose one supplier from the top-level members randomly
for all round do
    Clients receive shipments shipped two rounds earlier by suppliers
    Suppliers pay the cost of production and send shipments to their clients, totally
    or partially, prioritizing largest due orders
    Suppliers register stock on hand or total due
    Suppliers pay the cost of the stock on hand
    Suppliers receive orders made one round earlier by clients
    if end of contract then
        Suppliers update sales price
        Clients review peer trust and supplier trust based on shipments received
        Clients decide whether to keep or switch supplier, and which one to switch to
    end if
    Clients size and send request to their suppliers and pay the price set by these
    Factory scales and sends production order
    Suppliers receive payment for orders placed in the current round by new clients,
    who buy at the set price
end for
```

5.2 Implementation

The project was implemented in ReLogo [15], a domain specific language (DSL) for ABM which incorporates libraries and features of the Repast Simphony framework [2][1].

5.3 Fixed input parameters

In our experiments, 50% of agents with Popular profile and 50% with Greedy profile by SC level were combined, in order to determine which strategy prevails over the other if both are adopted by the same number of agents. Another parameter is the demand of the final consumers. For this work, we decided to use random demand: in each round, each final consumer obtains the number of units to be ordered from a uniform distribution, defined in the range of integers between 0 and 12, including the extremes. The other parameters were set emphirically, as shown in Table 2.

[1] The source available at Github, `https://github.com/ajalbut/SupplyChainTrust`.

Table 2: Fixed parameters

Parameter	Description	Value
D	Simulation duration in rounds	200
d	Supply contract duration in rounds - Section 4.7	10
L	Agents per SC level	20
S*	Desired (safety) stock - extracted from [17]	48
p	Production cost - Section 4.4	10
α_s	used in stock adjustment - extracted from [17]	0,5
β	α_{sL}/α_s - used in supply line adjustment - extracted from [17]	1,0
Θ	used in demand forecast - extracted from [17]	0,5
N	used in supplier choice - Section 4.7	5
δ	differentiates prices between profiles - Section 4.7	0.25

5.4 Experiment 1: impact of peer recommendations

In this experiment, all agents were programmed to tell the truth (liar rate $\lambda = 0$), and were subjected to different suggestion rate values (ϵ ranging from 0.0 to 1.0 with 0.1 increment). Each scenario was executed 20 times, and both the mean and standard variation of working capital and trust values at the end of the simulation are shown respectively in Tables 3 and 4.

Table 3: Working capital per suggestion rate ϵ

Profile	ϵ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Popular	μ	76321	96719	118691	131345	132885	136331	139479	136200	135628	135707	131964
	σ	18002	15202	13511	13039	9007	12359	16474	11269	11986	11599	11414
Greedy	μ	98201	74436	49485	36513	35960	30326	27798	32063	29595	28459	29644
	σ	16861	14563	12716	13218	9160	10977	14044	10327	12047	11035	11637

Table 4: Trust per suggestion rate ϵ

Profile	ϵ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Popular	μ	0.792	0.778	0.753	0.741	0.728	0.705	0.710	0.701	0.695	0.662	0.637
	σ	0.017	0.024	0.032	0.031	0.036	0.031	0.046	0.031	0.039	0.036	0.042
Greedy	μ	0.494	0.493	0.471	0.459	0.439	0.409	0.414	0.415	0.383	0.391	0.370
	σ	0.031	0.048	0.040	0.030	0.042	0.041	0.045	0.039	0.029	0.046	0.050

We can verify that when suggestion rate ϵ increases, working capital tends to increase for popular agents and decrease for greedy ones. A possible reason is that in the long run both popular and greedy agents tend to go for popular suppliers, the first ones aiming for higher trust rates to guarantee their client deliveries and the latter aiming for lower purchase prices to reach higher profit margins. As a consequence, all tend to migrate in the course of simulation. With more sincere reccomendations, they gather supplier information faster than exploring on their own, resulting in faster migration and more clients for popular agents.

Moreover, if we analyze some particular cases, when high suggestion rates ϵ effectively generate supplier switching, frequently suppliers do not deliver their goods on time, since it becomes harder for them, whatever their profile is, to predict demand and keep up with orders.

Fig. 3: Difference between low and high suggestion rate ϵ

(a) $\epsilon = 0$ (b) $\epsilon = 1$

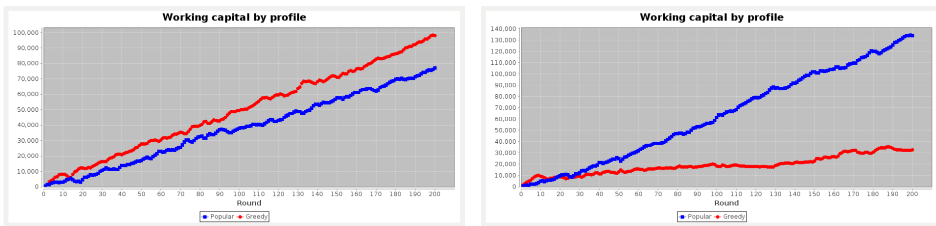

Figure 4 illustrates working capital difference between popular and greedy agents in two different individual simulations. When there are no supplier suggestions from peers ($\epsilon = 0$), greedy agents (red line) profit more than popular agents (blue line). On the other hand, when agents always ask for supplier suggestions ($\epsilon = 1$) greedy agents start off better, but are quicky surpassed by popular ones.

5.5 Experiment 2: impact of lies

In this experiment, 5 different liar rates were tested (λ ranging from 0.0 to 1.0 with 0.25 increment), combined with 3 different suggestion rates (ϵ equal to 0.25, 0.5 and 0.75), for a total of 15 scenarios. These ϵ values were chosen to represent typical proportional values. Again, each scenario was executed 20 times, and both the mean and standard variation of working capital and trust values at the end of the simulation are shown respectively in Tables 5 and 6.

Table 5: Experiment 2

(a) Working capital per liar rate λ

ϵ	Profile	λ	0.00	0.25	0.50	0.75	1.00
0.25	Popular	μ	118864	116425	109623	91447	85634
		σ	14015	14831	16615	13685	20361
	Greedy	μ	49943	53629	64251	81429	90008
		σ	13659	13286	14932	13699	19394
0.5	Popular	μ	133481	119813	113035	96434	69591
		σ	13406	13987	12019	16804	17042
	Greedy	μ	33453	49698	57569	78974	107241
		σ	11268	13554	11930	16466	15968
0.75	Popular	μ	137345	125819	106664	98942	52685
		σ	12219	12062	17864	13475	14259
	Greedy	μ	28338	43509	64837	75231	123477
		σ	10411	11617	17049	10316	14490

(b) Trust per liar rate λ

ϵ	Profile	λ	0.00	0.25	0.50	0.75	1.00
0.25	Popular	μ	0.753	0.769	0.785	0.781	0.792
		σ	0.033	0.022	0.025	0.025	0.025
	Greedy	μ	0.459	0.471	0.482	0.505	0.515
		σ	0.039	0.053	0.039	0.035	0.034
0.5	Popular	μ	0.727	0.734	0.770	0.783	0.789
		σ	0.045	0.043	0.032	0.032	0.018
	Greedy	μ	0.433	0.453	0.464	0.498	0.502
		σ	0.038	0.038	0.043	0.038	0.043
0.75	Popular	μ	0.683	0.717	0.737	0.776	0.774
		σ	0.041	0.025	0.039	0.024	0.031
	Greedy	μ	0.414	0.446	0.441	0.468	0.488
		σ	0.026	0.037	0.031	0.046	0.036

Table 6: Experiment 2

(a) Working capital per liar rate λ

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	Greedy	μ	0.414	0.446	0.441	0.468	0.488
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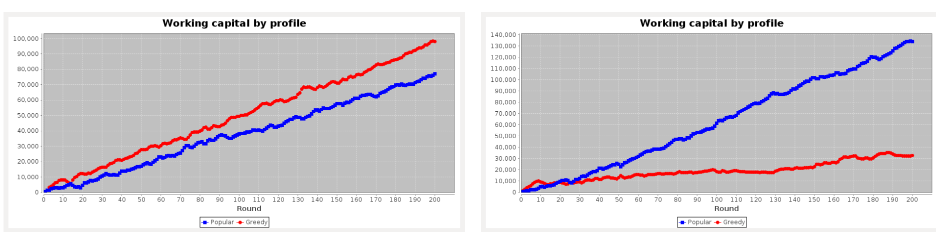
Regarding the working capital, it is possible to observe that a higher proportion of liars benefits greedy agents and impairs popular ones, since the false recommendations provided by liars tend to point to expensive and unreliable suppliers, which are mostly greedy.

Considering each profile, either popular or greedy, the impact of higher liar rates λ is more significant at higher suggestion rates ϵ, in which case agents adopt suggestions more often and explore less on their own. This may be seen in Figure 4.

Fig. 4: Difference between low and high suggestion rate ϵ

(a) $\epsilon = 0$ (b) $\epsilon = 1$



When it comes to trust, popular agents tend to achieve higher levels when there are more liars, and greedy agents when there are less. As it occurred in Experiment 1, it becomes harder for suppliers, whatever their profile is, to predict demand and keep up with orders. Moreover, like the results obtained in Experiment 1, trust level decreases when suggestion rate ϵ increases.

6 Conclusions

In this work, a multi-agent approach was used to simulate a particular SC, namely the *Beer Game*. In the experiments, it was possible to observe the effect of different agent's strategic profiles on their average individual profit. Trust-based client-supplier relationships tend to thrive when there is plenty communication and sincerity, while price-based decisions prevail when silence and/or lies are the norm.

For future experiments, it would be interesting to evaluate the individual benefits of lying compared to telling the truth, as well as to analyse unequal proportions of popular and greedy agents, different supply chain topologies and different values for Beer Game parameters. We could also enable requesting agents to order goods simultaneously from multiple suppliers in a same round. It would be also interesting to test different consumer demand models, instead of just using a random model.

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