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COMPLEXITY ANALYSIS THROUGH THE MODELING OF HUMAN BEHAVIOR IN A COMPLEX SUPPLY CHAIN PLANNING ENVIRONMENT

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ABSTRACT

The global supply chain is a complex network including multiple autonomous agents, and one representative of which is the supply chain planers, whose interactive activities bring in various uncertainty and complexity to the decision making. To better manage the dynamics, it is necessary to investigate the agents behaviors and their impacts on the supply chain. Our research starts with some hypotheses and then verifies them via an experiment. A prior questionnaire is distributed in order to analyze the correlation between human performance and risk literacy scale. Then a beer game is employed to demonstrate the ordering behaviors under different environmental settings. The bullwhip effect and the overreacting behaviors are observed and can be illustrated by the prospect theory. Finally an agent-based modeling approach is adopted to simulate the human behaviors, using the empirical threshold values derived from the example as the inputs to the model.

1 INTRODUCTION

The global semiconductor and electronics supply chain is very sensitive to the changing macroeconomic environment. The goods, starting with the form of foundation materials such as silicon, flow from the raw material supplier to the semiconductor manufacturer (a.k.a tier 2 supplier), and then to the tier 1 and the original equipment manufacturer (OEM), and are delivered to the end-users as final products. Comparing with other tier 1 and OEMs, semiconductor firms are further away from the end consumers, which lead to even higher demand fluctuations.

Supply chain is viewed as a complex system consisting of a set of activities, agents, technological and physical infrastructures which interact with each other through information exchange and material flows in order to reach business goals (Rouse 2005, Sun et al. 2015b). It is also highly influenced by the environment. For a general supply chain its complexity can arise from a number of sources: network, process, product, organization, information and so on (Christopher 2010, Sun et al. 2015a).

Decision makers want to keep value-added complexity and reduce non-value-added complexity. Quantitative research on complexity drivers measurement has been investigated and some indices are developed, e.g., the product and information complexity (ElMaraghy et al. 2008, Schuh et al. 2013).

However, for the organization change complexity especially related to the human decision part, it is difficult to quantify. Therefore, our research focuses on this area and expect it could benefit the holistic complex system measurement. The research target is about the human behaviors and their impacts on the overall supply chain complexity. It contains several following research questions:

- The correlation between cognitive mechanism and human behaviors
- The performance of human behaviors under different settings of scenarios
- The critical behaviors in the supply chain, e.g., abnormal, dominant, or overreacting behaviors which contribute more complexity to the supply chain system
- The cost and benefit analysis on the added complexity caused by those critical behaviors

The objective of this paper is: 1) To verify the hypotheses related to the human behaviors, bullwhip effect and the system complexity, and 2) To propose a trial approach for the further investigation on the human behaviors simulation using the agent-based modeling approach.

This rest of this paper is structured as follows. In Section 2 the related literature is discussed. In Section 3 the hypotheses are highlighted in the beginning; then an experiment for verification purpose is set and implemented; the results are thus analyzed and hypotheses are evaluated; followed by an example of simulation model. We conclude in Section 4 and also give the directions for the future research.

2 THEORETICAL FOUNDATION

The bullwhip effect refers to the tendency of orders to increase in variability as it moves up the supply chain (Lee, Padmanabhan, and Whang 1997; Croson and Donohue 2003). One crucial cause of this effect is the insufficient coordination among supply chain partners, which leads to the individual's decisions biases and deviated ordering behaviors because of lacking the complete information or comprehensive understanding of the overall supply chain. It is harmful to the supply chain especially for the partner far away from the end customer as it magnifies the upstream order, and thus leads to excessive inventories, unsatisfactory customer service, and uncertain production planning (Wu and Katok 2006). This uncertainty also induces the complexity of supply chain. From the complexity management view, the increased fluctuation and amplification parts do not add values at all. Therefore the non-value added complexity caused by the bullwhip effect should be eliminated or reduced.

The bullwhip effect is often demonstrated by the well-known beer distribution game, or is called beer game for short, including four supply chain echelons (Sterman 1989). It has a wide range of conditions (Steckel 2004), by setting the parameters, e.g., roles, delay time, the initial inventory, researchers can conduct their experiments for different purposes.

Several techniques are employed to mitigate the influence of bullwhip effect, with the help of the computer-based simulation techniques people can model the dynamics of the supply chains. From the perspective of collaboration mechanisms, the supply chain partners are encouraged to use some rational ordering strategies, e.g., information sharing with other echelons.

The research on human behaviors in complex systems is a multi-discipline includes the cognitive science, psychology, etc. The cognitive demand is defined by these dimensions: dynamism; the number of parts and the extensiveness of interconnections between the parts or variables; uncertainty, and risk (Woods 1988) .

The most popular theory for the prediction of decision-making under risk is known as the prospect theory (Kahneman and Tversky 1979; Kothiyal, Spinu, and Wakker 2014). According to this theory, in situations of decision-making under risk, losses have a higher emotional impact than the equivalent amount of gains. Taking the example of a supply chain planner, who needs to decide how much inventory to hold based on the forecasting of volatile demand, this is a situation with high risks in the day-to-day decision-making. This type of behaviors described by the prospect theory is often observed in the planning process but rarely addressed in modeling (Alexander, Walker, and Naim 2014).

One typical characteristics of prospect theory is the overreacting behaviors. In the bullwhip effect, it is defined as: agent places the order which is far deviated from the downstream demand. While in an ideal circumstance, agent is rational and should always order the same demand received from the downstream. However, if the quality of information sharing is poor, the agent tends to have irrational behaviors and thus the demand and placed order are not always matched, which sometimes lead to the cumulative effect of deviation. This phenomena exists in most scenarios especially in the non-collaborative group.

An important cognitive indicator for decision making is the risk literacy scale, which implies the ability to understand and make good decisions about risk (Cokely et al. 2012). Other indictors related to human's cognitive mechanism on the risk taking are also available, e.g., the risk perception, risk propensity (Keil et al. 2000).

3 MODELING OF HUMAN DECISIONS IN COMPLEX SUPPLY CHAINS

3.1 Hypotheses

Based on the above research questions and the literature review, the following hypotheses are formulated:

Hypothesis 1 *The subject's risk literacy is positively correlated with its performance in the game.*

Risk literacy is one of the major determinants of the performance of the human behaviors. The higher risk literacy a subject has; the better performance the player should have.

Hypothesis 2 *The complexity occurred in the beer game is mainly contributed by the overreacting behaviors of human, and this can be explained by the prospect theory.*

A well running (collaborative) supply chain system has predictable order behavior, while the behavior or pattern from a non-collaborative group is very difficult to predict and thus leads to the uncertainty of the whole system. Usually the order behaviors fluctuate within a limited area, however, when they reach certain threshold or receive some stimuli, they start to change dramatically, e.g., when the players notice the appearance of backlogs, they would order much more than necessary. These behaviors can be explained by the prospect theory.

Hypothesis 3 *There is a trade-off between increased complexity and cost-saving; via sharing information the overall complexity and cost can be changed.*

Comparing with the settings of two scenarios, the collaborative group has more communication complexity; while the non-collaborative group tends to increase the supply chain complexity due to its overreacting behaviors. Hence the complexity of those parts which may affected by setting changes needs to be evaluated.

3.2 Experiment

3.2.1 Experimental Design

The experiment is designed with two steps: the risk literacy questionnaire and the beer game session.

The questionnaire of risk literacy includes two parts. The first part is about the qualitative risk scale, here we adapt a Domain-Specific Risk-Taking (DOSPERT) scale, which is originally designed to assess the risk taking in five content domains (Weber, Blais, and Betz 2002). In order to keep the questionnaire short and simple for the practical purpose, we only choose the relevant domain of financial decisions with 7 items, which are shown in Appendix A. Respondents rate the likelihood that they would engage in the risky activities according to their perceptions of risks and benefits using a 7-point rating scale ranging from 1 (Extremely Unlikely) to 7 (Extremely Likely).

The second part adopts the Berlin Numeracy Test to quantify the statistical numeracy and risk literacy scale. It is considered as the strongest predictor of comprehension of everyday risks (Cokely et al. 2012).

To adapt to the business environment, we rename the two parts of the questionnaire: the risk tendency test and the cautiousness test.

The natural choice of the second step is the beer game, as it is simple enough for people to learn in a short time while retaining the key features of real supply chains (Croson et al. 2014). It is conducted on an online Beer game platform (Narayanan 2011) and the setting of supply chain is shown in Figure 1.

Six echelons from the end customer to the raw material supplier are included in the supply chain, the role of end-customer and the raw material supplier are set automatically, and the other four echelons: retailer, wholesaler, distributor and factory are performed by participants. The time delay between each echelon, the demand pattern and the initial inventory are also set in advance. The goal for the participants in a serial supply chain is to minimize the total inventory cost.

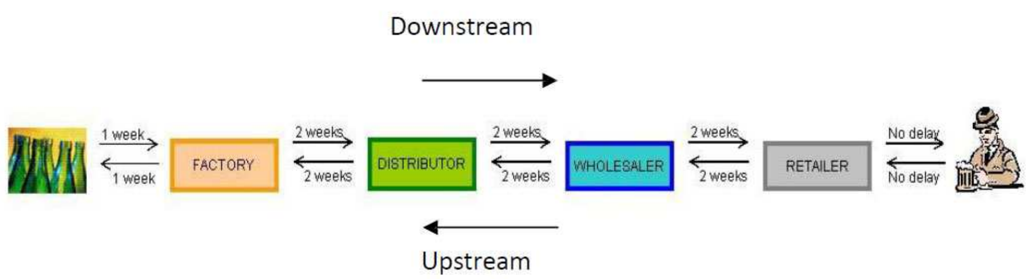

Figure 1: The Beer game settings (cited from Narayanan 2011).

The experiment is implemented within the corporate supply chain organization in an international company and 20 participants attend. All of them are the young talents from different cultural background with higher education and have some experience on the supply chain. They are divided into 5 groups, 2 of which are required to share the information (status of inventory, demand, placed order, etc.) in the game while the other 3 groups are not allowed to exchange information.

3.2.2 Key Indicators

We are interested in several indicators which can be used to evaluate the subjects' behavior and performance.

From the results of the risk literacy questionnaire in the first step, we can calculate two values for each subject:

- The risk tendency, which means the probability of subject's risk-taking
- The cautiousness, which represents the level of subject's cautiousness

We also derive some performance indicators from the beer game results which could help us analyze the subjects' behaviors:

- The deviation between the downstream demand and the placed order
- Demand quantity and variation
- Inventory quantity and variation

- Order quantity and variation
- The inventory cost

Using above indicators we can rank the performance of each subject and thus validate the hypotheses proposed in Section 3.1.

3.3 Analysis and Results

3.3.1 The Initial Analysis on Player Profiles

The risk literacy values for subjects are obtained from the results of questionnaire. The first part reflects whether people tend to take risks. Higher likelihood indicates greater risk taking in the financial decisions. A prerequisite here is the higher risk tendency means lower cognition for a subject and thus it is assigned to a lower score (Weber, Blais, and Betz 2002).

The results of the second part identify whether subjects are cautious when they make decisions. By rating the answers of these 4 items, we can get their cognitive cautiousness values in scale.

Some research (Cokely et al. 2012, Narayanan 2015) argues that the risk tendency value is correlated with the cognitive test values such as the Cognitive Reflection Test (CRT). However, from our results, there is no strong correlation between the two parts of questionnaire.

To mediate the risk literacy values, we simply add the scores of the 1st part (7-49) and the scaled scores of 2nd part (0-50). For each subject, we calculate their risk literacy. The higher value it is, the better decision making ability the subject has. Depending on the high or low value, we can classify a subject as the *risk-averse* or *risk-prone*.

Regarding the subjects' performance in the beer game, we choose two prevailing indicators: the order standard deviation and the inventory cost. For each subject, we consider one indicator from two dimensions: the rank of performance for the same role in all groups; the rank of performance within the same group. The performance score for each subject is between 0-14.

3.3.2 Hypotheses Verification

Based on the results from Section 3.3.1, we can check the correlation between the risk literacy and the performance. We thus draw the liner regression line for each collaborative or non- collaborative group in Figure 2. It is observed that 4 out 5 groups have shown the trend that the performance is positively related to the risk literacy scale. Although there is certain bias, we can still conclude that the higher risk literacy is, the better performance the subject has and thus the H1 is supported in general.

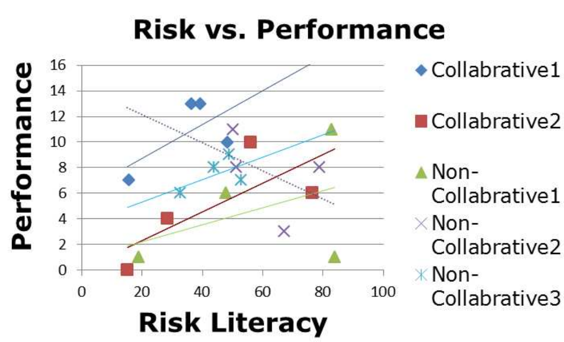

Figure 2: The correlation between the Risk Literacy and Performance.

The trends of the contrast groups also show that for the subjects in the collaborative group 1 who have relatively lower risk literacy values comparing with other subjects/groups, instead they can have very good performance when working as a group. This inference does not fit well for the collaborative group 2 due to the poor quality of information sharing in the game. Therefore, we conservatively conclude that with the help of information sharing the group which is categorized as less cautious can have better performance than the group with high risk literacy players but without communication.

For the H2, our analysis is about the ordering behaviors and their changes. We focus on the subjects' overreacting behaviors, which are shown in Figure 3 on an example of the factory agent. The highlighted triangle area is our interesting region. We would like to investigate the causes for the deviations between the real demand and placed order, and whether there is any patterns behind these overreacting behaviors .

In the ideal situation, the order quantity should always follow the trend of the downstream demand. However, the subject does not always follow this strategy due to lacking of the complete demand information or the overall supply chain picture, or even influencing by their own cognitive biases, thus the deviation arises and will be cumulated. This phenomena is especially evident in the non-collaborative scenarios, as shown in Figure 3. Whilst in the collaborative cases, some influencing factors can be eliminated or mitigated and thus the deviation is narrowed, and also of importance is the fact that the quality of information sharing and game strategy decide the degree of order-demand match.

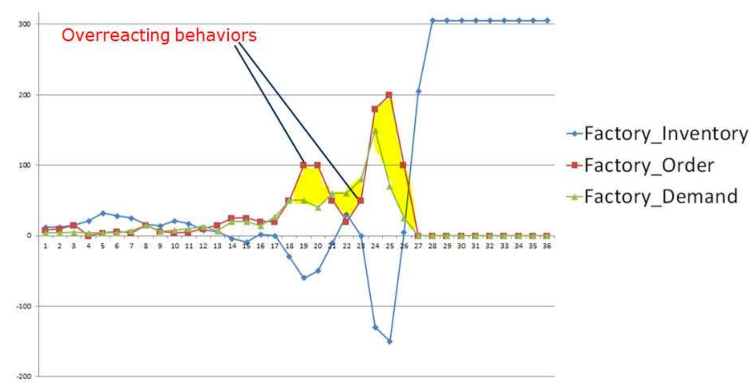

Figure 3: Overreacting behaviors and their added complexity under the non-collaborative setting.

From the observation, we notice the overreacting behaviors are more likely to happen in certain period of the game. In the beginning subjects play more stable and rational, but a few weeks later the abnormal behaviors may gradually appear, which are usually stimulated by certain events or signals, e.g., the huge inventory or backlog. Without a doubt the "cumulative effect" is also one factor. We summarize several triggers which could lead to the overreacting behaviors:

- Demand pattern changes. When subject does not realize the change of demand and still sticks to the old ordering strategy, the deviation arises.
- Inventory changes. When subject notices the inventory is increasing, they start to reduce the order quantity; vice versa.
- Forecasting the inventory or demand changes. When subject perceives the changing trend, they do the corresponding strategies in advance to alleviate the effect of the changes.

The first type of overreacting behavior is the passive result, while the other two are active reactions.

We are aware that, when the backlog emerges, subjects tend to order more in order to have sufficient amount of stocks. This action can be amplified when the backlog increases. At this point, if we analyze the quantity, it may be highly deviated from the average level. Many cognitive theories are employed to explain this phenomenon, and the prospect theory is one of the popular tools to describe the irrational behaviors (Kahneman and Tversky 1979).

To apply the prospect theory on our case, the first step is to look for the individual reference point (*status quo*) for each subject respectively. The physical meaning of status quo is that it is an equivalence point to balance the stock and backlog from the subject's perception. Each individual has his or her own status quo, for example, risk-adverse people tend to have more stocks, while the risk-prone people prefer to have less stock or even backlog. We define the stock as *Gains* and backlog as *Losses* for the outcome-axis, and set the order quantity for the value-axis. To make it simple, we use the ratio of inventory to the average demand as the variable on X-axis, and the ratio of order to the average demand as the variable on Y-axis. The status quo for each subject can be calculated from the beer game results. The value of the Y-axis reference point is the ratio of the average order to the average demand, and thus the reference point value on X-axis can be obtained using the regression function.

After setting the references we can draw the "prospect theory curve" for each subject. We select two contrast groups: a collaborative one and a non-collaborative one. The diagrams are shown in Figure 4. For each frame, the red dot is the reference point and the two red curves represent the trends of people's behaviors on "loss" and "gain". The linear line shows the virtue trend of the "gain" strategy if it would be followed in the "loss" area too. If subjects are pure rational, their behaviors should follow the straight line exactly.

For the players in the non-collaborative group, we can see their loss trend is much deeper than the gain trend, while the difference between the two trends is not obvious in the collaborative group. The figures show that the subjects with better information can make more consistent and moderate decisions, but without enough information they tend to have extreme decisions and express stronger loss aversion than gains. It is worth noting that one major feature of prospect theory is the diminishing returns characteristics, which is reflected on the loss trend of our results, but not on the gain trend.

Therefore, we can conclude for the H2, when there is backlog, the overreacting behaviors can be explained by the prospect theory.

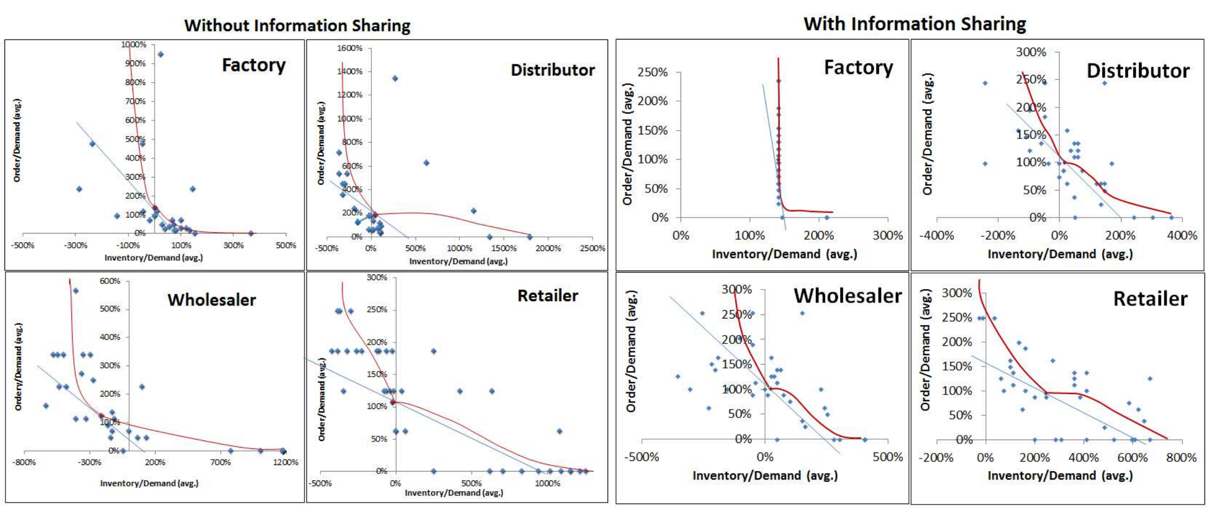

Figure 4: Order behavior based on the Inventory and Demand (with and without information sharing).

We also highlight the key indicators to detect the overreacting behaviors:

- The high absolute value of inventory/backlog
- The increase of inventory/backlog

- The sudden change of demand

Some preliminary investigation is carried out to classify the ordering behaviors under certain conditions. With the notice that subjects can change their behaviors when specific conditions are reached, we would like to set a group of threshold values for the behaviors indicators for roles at each echelon in the supply chain in order to understand their patterns. We thus design a 7-level ordering behaviors pattern linked to the risk tendency: high risk-averse (L1), medium risk-averse (L2), low risk-averse (L3), reference level (L0), low risk-prone (L4), medium risk-prone (L5) and high risk-prone (L6). For each level, we can set various numerical values for each indicator based on the characteristics of each echelon.

The conditions would be different according to the settings of scenarios. For the collaborative scenario, we find that among the three main deviation factors, the inventory/backlog value is rather indicative and the demand variation also show strong relevance for some behavior changes. While for the non-collaborative scenario, demand variation is the primary influencing factor and then comes to the inventory factor.

In Table 1 and 2, we list the conditions on an example of the wholesaler agent in different scenarios respectively. We denote S1 for the scenario without information sharing and S2 for the scenario with information sharing. Under the column of Conditions, the parameters "I" identifies the ratio of inventory to average demand; and Dv represents the demand variation.

For each scenario we have the corresponding ordering behavior defined for the roles with level L0-L6. For example, L4 in Table 1 means that when the inventory value is between -150% to 200% and demand variation is larger than 0, the order quantity is set as 120% of the demand. It is worth mentioning that all the conditions and behavior threshold values are only obtained from one example but not from the statistical results.

Table 1: Ordering behaviors with 7-levels with their conditions in S1 (wholesaler).

Behavior Level	Condition	Ordering Behavior
L0	Others	1
L1	I <= -4	3
L2	-4 < I <= -2	2
L3	-2 < I <= -1.5	1.5
L4	-1.5 < I < 2 && Dv > 0	1.2
L5	-1.5 < I < 2 && Dv < 0	0.8
L6	I > =2	0

Table 2: Ordering behaviors with 7-levels with their conditions in S2 (wholesaler)

Behavior Level	Condition	Ordering Behavior
L0	Others	1
L1	$Dv \geq 1$	2
L2	$1 > Dv \geq 0.6$	1.3
L3	$0.6 > Dv \geq 0.3$	1.2
L4	$-0.3 > Dv \geq -1$	0.8
L5	$-1 > Dv \geq -1.5$	0.5
L6	$Dv < -1.5$ or $I > 2$	0

We can get the similar tables for other echelons. These results can be used as the input for the simulation model in Section 3.4.

For the H3, we compare the complexity and cost of the two scenarios. From the cost perspective, it has been proved that the collaborative group can have much lower supply chain cost. However, from the experimental settings and observation, we also realize that the complexity of this scenario increases significantly comparing with the non-collaborative group. Therefore we would like to analyze the added complexity from S1 to S2 and whether the saving cost could offset the added complexity.

The complexity drivers in this case are mainly the processes increased, therefore our analysis focus on the adding parts: the more communication and interaction between agents; the longer decision making processes, etc. Using the costs benefits analysis, we could conclude that although the collaborative scenario increases certain degree of complexity, but it could save much more cost on the inventory. Therefore the H3 is supported here.

3.3.3 The Limitations of the Experiment

Our hypotheses are founded on the empirical data collected from the beer game, which supports our hypothesis somehow; however, the weakness of this experiment should be pointed out:

- The small sample size might weaken the statistical significance results.
- The questionnaire is implemented slightly different with the original design, which requires translating the questions into the subject's native languages, while we only used the English version and many subjects are non-native English speaker. Besides that, we did not distinguish the risk literacy scale, culture, or nationality when we assigned the subjects into different groups.
- The experiment setting did not cover all controlling factors for the contrast group, e.g., some subjects with experience on this game may have better performance than non-experienced ones.
- The 7-level behaviors threshold values are only an example to represent the first step results; a more generic way to calculate the values is needed in the future.

3.4 Simulation Model for the Multi-Echelon Supply Chain

To better understand the individual human behaviors, their interactions and effects on the whole supply chain, we consider using the simulation techniques to model the agent behaviors, which provide a computer-based method to analyze various scenarios with changeable settings over time.

Agent-based simulation (ABS) is an appealing approach to model the decision-making process of autonomous agents and their social behaviors and interactions within an organization. The agent-based modeling (ABM) is commonly applied in the supply chain management (Macal and North 2013). Therefore we adopt the ABM to build an agent-based model with the purpose to simulate the long-term trends of supply chain planers behaviors under different scenarios.

In our model design, the agents are corresponding to the four echelons, and the agent relationships and interactions are decided by their positions in the down-stream and up-stream. For each agent, we define their rules and patterns, which mean the ordering behaviors under different situations and the triggering points to change behaviors.

For the implementation, we use the threshold values obtained from Table 1 and 2 as the parameters, and the input demand of end customer is the real data from semiconductor market. The output is the ordering quantity for each agent. Since we are also interested in the relationships among order quantity and other variables such as inventory and demand, we address three key indictors in the results analysis: the ratio of inventory to demand, the demand variation and order quantity.

For each echelon, we can get its variables information and draw the trend diagrams from the empirical results. We choose wholesaler as an example and illustrate its behaviors in Figure 5. It shows wholesaler's three key indicators and their trends under the collaborative and non-collaborative scenarios respectively. From the picture it is clearly to see that the demand variation and order quantity in S1 have higher fluctuation than those in S2, which is the same for the inventory. This phenomenon has been explained in the theory part and now is validated by the empirical results.

One advantage of using simulation is that we can easily tune the parameters in the experiment. By setting the different threshold values, we can compare the trends and effects of agent behaviors under various triggering points and thus support decision making in the supply chain planning.

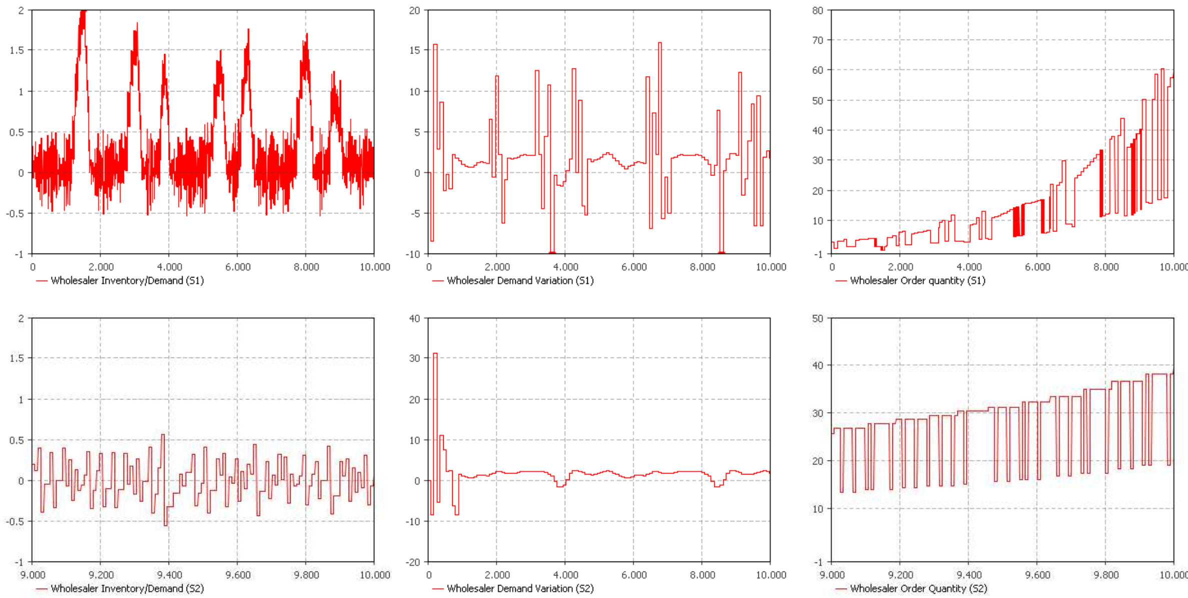

Figure 5: The Inventory, Demand variation and Order diagrams for S1 and S2 (wholesaler).

4 CONCLUSION AND NEXT STEPS

In this paper we propose the hypotheses related to the human behaviors and performance in a complex supply chain and verify them via a conducted experiment which includes a questionnaire and the beer game. We discuss the correlation between risk tendency and cautiousness; the risk literacy and the performance. We observe the bullwhip effect and detect the overreacting behaviors which can be explained by the prospect theory. The role of information sharing is addressed and proved to be efficient in cost saving. The system complexity is compared for different scenarios and settings. Apart from that, we also show a preliminary procedure to detect and predict the overreacting behaviors. The ABS as a powerful modeling approach is highlighted in the end.

Here we give directions for the future research. An experiment with more samples is planned to be conducted in order to gain statistical significance. For the overreacting behaviors detection and prediction, we can develop a more mature approach to calculate the threshold values based on the large sample data. We also consider investigating on the other potential factors which might lead to the overreacting behaviors, e.g., long delivery time. Furthermore, we would like to evaluate the influences of the overreacting behaviors on the overall supply chain and thus measure their complexity.

A APPENDIX RISK LITERACY SURVEY

The survey includes two parts. The first part is as below:

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation.

1 - Extremely Unlikely 2 - Moderately Unlikely 3 - Somewhat Unlikely 4 - Not Sure 5 - Somewhat Likely 6 - Moderately likely 7 - Extremely Likely

1. Betting a day's income at the horse races:

2. Investing a day's income in a moderate growth mutual fund:
3. Betting a day's income at a high-stake poker game:
4. Investing a day's income in a very speculative stock:
5. Betting a day's income on the outcome of a sporting event:
6. Investing 10% of your annual income in a new business venture:
7. Taking a job where you get paid exclusively on a commission basis:

For the second part of the survey, the Berlin Numeracy Test, it can be found through this link: Measuring Risk Literacy: The Berlin Numeracy Test: http://journal.sjdm.org/11/11808/jdm11808.html

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