The impact of risk preferences on supply chain performance

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Abstract

In this paper, we explore the impact of risk aversion on inventory management in multi-echelons supply chains and the ensuing dynamics of supply chains. The literature on the impact of risk aversion on supply chains is quite limited and, in particular, there is no evidence concerning the impact of: (1) individual risk aversion on inventory holdings and supply chain dynamics (e.g. order patterns and inventory stability); (2) possible combinations of risk aversion (*i.e.* high vs. low) across the supply chain on the performance of the chain as a whole. We explore these gaps through a multimethod approach (*i.e.,* human experiments and Agent Based Simulation), thus using both empirical and simulated data. Results show that risk aversion significantly influences supply chain dynamics.

Keywords: Risk aversion, human experiment, multi agent based simulation

Introduction

Risk aversion (RA) refers to the posture of a decision maker who is willing to accept a lower but sure monetary outcome instead of a higher but riskier outcome (Pratt, 1964). Therefore, risk averse decision makers will naturally tend to avoid risky situations and prefer certainty, albeit at higher costs. In the fields of supply and inventory management, the implicit assumption is generally that of “risk neutrality”, implying that professional decision makers always choose on the base of the expected value of payoffs or returns from a decision. However, empirical results from neighboring disciplines such as economics and psychology (Rabin and Thaler, 2001) suggest that RA is widespread in consumption, investment, and production, thus recommending the investigation of its impact on human decisions also within operations management.

Indeed, the stream of literature incorporating the hypothesis of a risk averse decision maker in supply and inventory management models finds that RA may have significant effects on decisions and performance. For instance, in a model of the risk averse newsvendor, the risk-averse decision maker will order less than the risk-neutral one, thus causing lower profits and inefficiency (Agrawal and Seshadri, 2000a; Eeckhoudt et al., 1995). Gavirneni and Robinson (2014) show that RA coupled with shortage costs can explain anchoring and insufficient adjustment in the newsvendor problem. RA also affects sourcing strategies (Giri, 2011), and may cause coordination failures within supply chains (SC) (Choi et al., 2008). Finally, if agents exhibit RA, this requires ad hoc contractual agreements that introduce risk sharing among SC members (Agrawal and Seshadri, 2000b; Chen and Seshadri, 2006).

In spite of the potential relevance of RA on SC decisions, there is still a lack of empirical research, especially in multi-echelon SCs. This gap is partially motivated by the sheer fact that reconstructing RA from actual supply and inventory decisions is not easy, nor it is to monitor real life supply and inventory decisions of risk averse managers across the SC. For this reason, this paper adopts both human experiments and agent-based simulation to investigate how RA affects order quantities and inventory management in a four-echelon serial SC.

Specifically, the two methodologies are combined as follows within the study. In the first step, in line with other SC experiments (Croson et al. 2014), we generate data on inventory decisions in a multi-echelon chain through a laboratory HE in which SC professionals participated as human subjects. Results from the HE are used to infer how individual risk aversion impacts on the behavior and performance of the individual SC members (*i.e.*, how orders are placed and which effects orders have on inventory holding costs). In particular, HE experiments suggest the hypothesis that higher risk aversion gives rise to higher inventory holdings and to a higher safety stock factor (SSF).

In the second step of our study, the HE results and the hypothesis generated are used to inform a MAS model, which extensively explores the dynamics of SC performance according to the risk aversion of its members. More specifically, we test the effects on the operational performance and customer service level of several combinations of risk averse members (*i.e.* several combinations of SSF setting) in each stage of a multi-echelon SC. The operational performance is assessed in terms of bullwhip effect (Lee et al. 1997, Chatfield et al. 2004) and inventory levels along SCs, while the customer service level is assessed in terms of fill rate at the retailer stage.

Therefore, our contribution innovates with respect to the extant literature in two respects: (i) we throw prima face empirical evidence on how individual risk aversion can affect orders and inventory holdings in a multi-echelon, multi-period SC; (ii) we adopt human experiments as a hypothesis generation tool, and use MAS to explore in greater depth the impact on SC dynamics in a four-echelon chain of various combinations of risk aversion within the SC.

Human experiment

The human experiment represents a first step through which individual RA is measured, and the behavior and performance of the members of a four-echelon SC based on their RA score can be observed. Participants in the experiment were purchasing professionals recruited in the course of an international business meeting on purchasing and supply management. Prior to the SC experiment, participants were required to answer a test made up of two correlated items intended to measure the extent of RA on a four-point scale (Barsky et al., 1997). Participants were then randomly assigned to a four-member group to play the co-called Beer Game (Sterman, 1989), meant to exemplify a serial SC with four echelons: factory, distributor, wholesaler and retailer. Players' task was to place an order upstream in each of the 35 periods of the game. Each player was assigned a specific echelon/role and he/she was in contact only with the closest downstream and upstream tiers. Players participated in two repetitions of the game (G1, G2), in order to observe whether the effects of RA were resilient to hands-on experience.

Figure 1 shows median inventory holdings per echelons (median over periods and over players) in the second repetition of the Beer game for high RA (score ≥ 3) and for low RA (score ≤ 2) players, showing that, except for the retailer who fully observes the external customer demand, low risk averse players exhibit higher median inventory (difference statistically significant by a Mann-Whitney test).

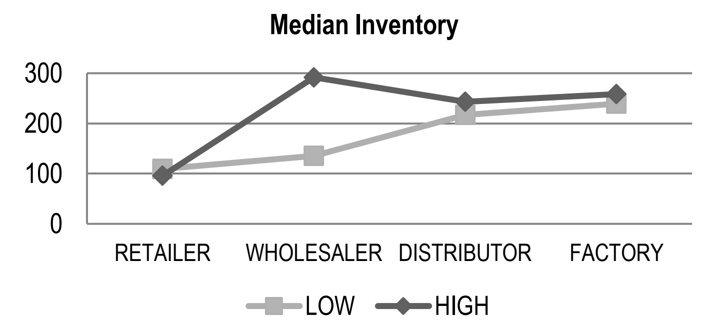

Figure 1 - Median Inventory (Low vs. high risk aversion)

The finding that individual risk attitude leads to higher average inventory holdings suggests that RA may be positively correlated to the desired stock and therefore with the safety stock factor (SSF), also known as Z-score. Therefore, we formulate the following testable hypothesis:

- *Hypothesis: Risk aversion is positively correlated with the desired safety stock factor*.

In the following section, this hypothesis will be fully explored through agent based simulations.

Agent based simulation

In real-life, the dynamics of orders, level of desired inventory, and expected fill rate are obtained by tuning parameters of order policies. Particularly, if a manager wishes to keep the inventory high and avoid stock outs, she/he may simply choose a high value of the SSF. Thus, it may be argued that managers with high RA would set high values of SSF. Based on this hypothesis, we explore how the order quantity placed by SC partners characterised by different RAs may affect the dynamics of the entire SC, specifically by testing in a multi-echelon structure the effects of several combination of SSFs. To fulfil the research objective, we adopt a quantitative model-based approach driven by the empirical findings of our human experiment.

In particular we model SCs through SCOPE (Dominguez et al. 2015), a multi agent-based (MAS) software platform specifically designed to overcome the shortcomings of traditional methodologies in SC modeling, and allowing the simulation of large SCs with complex configurations and uncertainties, which are more similar to real systems. The simulator was implemented using Java-Swarm, a well-known software platform for agent-based system development. SCOPE has been validated by confirming the results from previous simulations carried out by other authors with different methodologies (*e.g.* Chen et al. 2000, Dejonckheere et al. 2004 and Chatfield et al. 2004).

The performance of SCs is assessed in terms of operational efficiency and of customer satisfaction. Specifically we adopt two metrics, whose reduction reflects the improvement in cost effectiveness of members' operations (Cannella et al. 2013), *i.e.*, Bullwhip Slope (BwSl) and Systemic Average Inventory (SAI). The customer service level is computed through the Fill Rate. BwSl and SAI provide insights on internal process efficiency (*i.e.*, members' operational costs) of the whole SCs, while the Fill rate assess the final customer service level (Duong et al. 2015).

In analogy with the human experiment, we adopt the well-recognised "gold standard" multi-echelon model of SC literature, *i.e.* the four-echelon serially-liked SC under order up to policy composed by one Retailer (R), one Wholesaler (W), one Distributor (D), and one Manufacturer (M) (see, *e.g.*, Sterman 1989, Chatfield et al. 2004, Dejonckheere et al. 2004, Chatfield 2013, Croson et al. 2014, among others). To generate a SC model that comes closer to the true characteristics of real-life SCs, we carefully adopt assumptions based on insight from both axiomatic and empirical research. For further details on the adopted model, see Dominguez et al. (2015). The factors to be analysed are the SSF in each echelon of the SC. In order to obtain more general results, we use two intervals of possible values for each level instead of a fixed value. Specifically, we assume that a low RA may be represented by placing order with a Z-score contained in the range [0.26, 1.28] equivalent to a customer service level between 60% and 90%. The high RA is reproduced with a Z-score within the interval of [2, 3], *i.e.* customer service level between 97.72% and 99.99%. In each replication, Z-scores are chosen randomly among all possible values within the two intervals. We exclude from the analysis Z-score modelling a service level between 90% and 97.72% as they emulate a rational and commonly recommended implementation of inventory control policy (see *e.g.*, Ponte et al. 2017).

We perform a total of 16 different experiments (4x2x2), corresponding to 16 different SCs structure, and 30 replications for each experiment, obtaining a total of 480 simulations. Each experimental point focuses on a combination of RA (*i.e.*, high (h) and low (l)) across SC echelons. We identify the following 5 categories of RA in the 16 analysed SCs:

- *Full Low Risk Aversion*: all echelons with low RA (1 structure),
- *Medium-Low Risk Aversion*: three echelons with low RA and one echelon with high RA (4 structures),
- *Medium Risk Aversion*: two echelons with low RA and two echelons with high RA (6 structures),

- *Medium-High Risk Aversion*: three echelons with low RA and one echelon with high RA (4 structures),
- *Full High Risk Aversion*: all echelons with high RA (1 structure).

Simulation results and discussion

The results of the simulations are reported in Table 4 for each metric. Firstly, by focusing on operational performance (*i.e.* BwSl and SAI) we may argue that, as the number of partners characterised by high RA increases the performance of the whole SC linearly worsens. The best configuration in terms of operational performance is the SC composed by members with low RA, *i.e.* Full Low Risk Aversion SC, while the worst scenario is experimented by the Full High Risk Aversion SC. In general, we note that as one of the members turns into high risk adverse, the whole SC reports a deterioration of the operational performance. In fact, by shifting from the Full Low Risk Aversion SC to a Medium-Low Risk Aversion, BwSl and SAI reports a percent increase between [18%-27%] and [63%-71%], respectively. The analogous trend is presented by shifting from any SC configuration to another in which one of the members turns high risk adverse. Interestingly, the deterioration of the performance is linear. Figure 1 reports the mean values of BwSl and SAI for any RA category in which tendency lines of BwSl and SAI values record a R2=0.98 and R2=0.99, respectively. We note a further interesting insight by analysing the SCs belonging to the Medium-Low Risk Aversion category. In most of the cases, there are not relevant differences between SC structures characterized by the equal number of high (or low) RA partners. This consideration emerges by comparing the performance of the Medium-Low Risk Aversion SCs. The four structures are characterised by three echelons with low RA and one echelon with high RA and present almost identical performance. However, as we move to Medium Risk Aversion and Medium-High Risk Aversion, we note a minor increasing discrepancy among results. Conversely, the Medium-High Risk Aversion SCs presents a peculiar result. The structure *R(h)_W(h)_D(h)_M(l)* reports an increment of BwSl of 12% with respect to the *R(l)_W(h)_D(h)_M(h)*. This result may be explained through the empirical and analytical findings regarding the demand signal processing in SCs (Lee et al. 1997). The *R(h)_W(h)_D(h)_M(l)* is composed by three downstream adjacent partners with high RA. Their orders are certainly characterised by a relevant variability, as they desire to maintain higher inventory levels. Thus, the variability of orders is amplified at the lower stage of the SC (retailer), reinforced by two subsequent overactive partners (Wholesaler and Distributor) and finally managed by the unique members with low RA. In the other three SCs belonging to this category, this amplification is smoothed because there are no more than two consecutive partners with high RA or because the retailer is low RA and smooths from the beginning the demand amplification.

Now we focus on the customer level performance. We note a different trend with respect to the operation performance, where SCs belonging to the same category present similar outputs. Herein, in the same category we note SCs with extremely different Fill rate values. However, it may be found two specific behaviour patterns in the analysed SCs. All configurations with a Retailer low risk adverse present a fill rate between 90.99% and 93.25%, contrarily to SCs with Retailer high risk adverse where fill rate is not lower than 99.95%. These results would suggest that SC with high RA retailers always perform well in term of customer service level, regardless the RA of other members.

Finally, in the light of our results, we consider that the best configuration is the R(h)_W(l)_D(l)_M(l), in which only the retailer is high RA. This structure may represent a reasonable compromise between customer service level and operational costs.

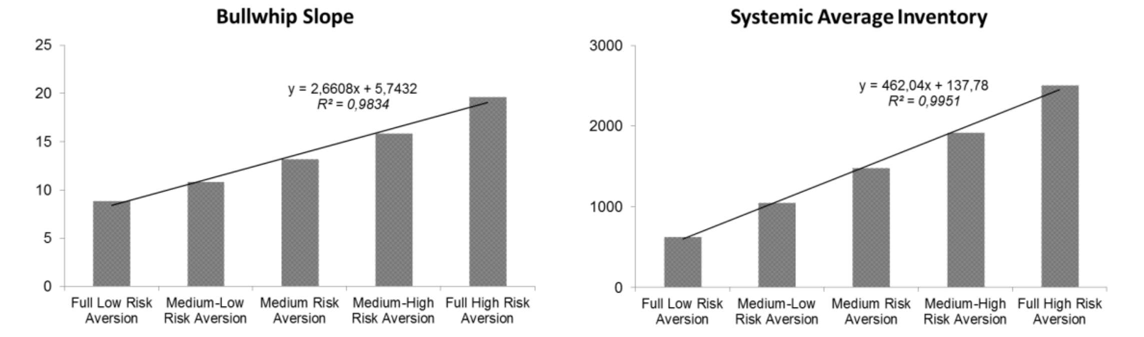

Figure 2 - BwSl and SAI of each category.

Table 1. Simulation output.

		Bullwhip Slope	*Systemic Average Inventory*	*Fill Rate*
Full Low Risk Aversion	R(l)_W(l)_D(l)_M(l)	8,89 ± 0,17	636,6 ± 50,7	92,60 ± 1,53
	R(l)_W(l)_D(l)_M(h)	10,47 ± 0,45	1061,8 ± 71,2	92,90 ± 1,73
	R(l)_W(l)_D(h)_M(l)	10,93 ± 0,31	1037,6 ± 66,7	92,80 ± 1,38
	R(l)_W(h)_D(l)_M(l)	11,32 ± 0,36	1044,0 ± 48,0	93,25 ± 1,45
	R(h)_W(l)_D(l)_M(l)	10,93 ± 0,21	1089,9 ± 36,0	99,95 ± 0,03
	R(l)_W(l)_D(h)_M(h)	12,72 ± 0,31	1457,4 ± 63,4	92,24 ± 1,43
	R(l)_W(h)_D(l)_M(h)	13,23 ± 0,65	1437,8 ± 64,8	92,03 ± 1,73
	R(h)_W(l)_D(l)_M(h)	12,34 ± 0,23	1503,7 ± 44,3	99,97 ± 0,02
	R(l)_W(h)_D(h)_M(l)	13,96 ± 0,38	1462,7 ± 49,8	92,56 ± 1,50
	R(h)_W(l)_D(h)_M(l)	13,62 ± 0,40	1556,0 ± 64,8	99,97 ± 0,01
	R(h)_W(h)_D(l)_M(l)	13,33 ± 0,30	1493,7 ± 56,8	99,97 ± 0,01
	R(l)_W(h)_D(h)_M(h)	15,77 ± 0,54	1781,8 ± 75,1	90,99 ± 1,75
	R(h)_W(l)_D(h)_M(h)	15,21 ± 0,56	1892,1 ± 84,2	99,96 ± 0,02
	R(h)_W(h)_D(l)_M(h)	15,37 ± 0,40	2026,2 ± 87,5	99,97 ± 0,02
	R(h)_W(h)_D(h)_M(l)	17,17 ± 0,52	2006,6 ± 88,3	99,98 ± 0,02
Full High Risk Aversion	R(h)_W(h)_D(h)_M(h)	19,71 ± 0,85	2512,6 ± 89,8	99,97± 0,02

Implications: theory and research on inventory decisions and SC dynamics

The results from this study offer relevant implications for the theory and practice of inventory and SC management. The HE has shown that in inventory management problems occurring within a SC channel, higher individual risk aversion leads to larger order quantities and to higher inventory at each specific echelon. This finding supports theoretical models of inventory management and order quantity choice that have analytically demonstrated that risk attitudes matter for supply decisions (*e.g.*, Eeckhoudt et al. 1995). Our findings do not confirm Eeckhoudt et al. (1995) who predict lower orders for standard risk averse newsvendors (single echelon, no inventory, no shortage costs) but confirm Gavirneni and Robinson (2017), who find that in the presence of shortage costs, the risk averse manager may order more than the risk neutral one. Furthermore, our estimated model suggests that, in an order-up-to model, the desired stock may be an increasing function of risk aversion, thus indicating a possible modelling avenue through which risk aversion could be incorporated in analytical models.

The MAS model, by treating the SSF as an echelon specific variable with a behavioural origin, allows extending the analysis of SC dynamics to the case of heterogeneous inventory strategies (*e.g.*, service level maximization vs inventory cost minimization) across the chain. In this fashion, this work provides two specific implications for researchers. First, it reasserts that simulation models hold the promise to complement empirical research in operations management (see Linderman et al., 2016). As recently advocated, using simulation models to see how people respond to complex situations and decisions (Croson et al. 2014) or using a case study to inform the development of a simulation model, represent new powerful emerging methods to develop more novel theories in operations management, especially when such theories are difficult to study using traditional empirical methods (Linderman et al. (2016). Secondly, it contributes to a relatively new research stream on SC dynamics, aimed at shedding light on the impact of new modeling assumptions on the results of classic SC models (see *e.g.*, Syntetos et al., 2016). This new research stream is motivated by the need of better capturing the increasing complexity of emerging new global SCs, such as modelling managerial judgement in replenishment practices. Empirical studies show that purchasing managers usually regulate judgmentally the order policy (Syntetos 2016 and references herein). That is, they judgmentally parameters of the adopted forecast method, safety stocks factors, etc. In this study, a new modelling assumption builds on a judgmental intervention on inventory stock factor related to the risk aversion of the decision maker. By doing so, we contributed to this new stream of research by showing how, "ceteris paribus" and depending on the judgmental intervention of the inventory manager, a classical order up to level may provide very different operational costs and customer service level in a multi-echelon SC.

Finally, in terms of SC dynamics, this study provides a specific advance to the current state-of-art. Models adopted in bullwhip effect analysis generally assume that SSF is fixed. Typically, a predetermined value that ensures a high customer service level or optimizes the inventory level, and identical for all SC members (see *e.g.*, Chatfield and Pritchard 2013), is adopted. In this work, we assume heterogeneous SSFs along the SC, as consequence of the different risk postures of SC participants. By doing so, we are able to provide insights on bullwhip effect, inventory costs and customer service level when SC members adopt different SSFs.

Implications: practitioners in inventory management policy

From a managerial viewpoint, results from this study may be used to inform different actions concerning the efficiency and customer responsiveness of replenishment decisions within a SC. In many business settings, people are selected based on their stated (or behaviourally revealed) risk attitudes. For instance, risk seeking individuals are considered to be more apt to manage new business ventures. The results of this study suggest that highly risk averse inventory managers are better suited to handle situations where the company requires a “prudent” inventory management behavior, and is willing to accept larger inventory holdings and lower net working capital in order to guarantee a high customer satisfaction level. Therefore, considering the individual echelon, the study implies that a company facing problems of high inventory days-on-hand (for instance with respect to their benchmark) should favor low risk aversion inventory managers, as instrumental to lowering stock and improving net working capital.

Given that total holding costs will also be a function of unit inventory costs, the impact of a high risk averse inventory manager may be mitigated by low unit holding costs (e.g., because of low obsolescence or low unit value). Conversely, fast obsolescence products require a low risk averse inventory manager.

The MAS model has also allowed the exploration of the performance of different SC structures according to the degree of risk aversion. Results on SC performance line up with conclusions at the individual level, since an increasing number of highly risk averse echelons amounts to higher systemic inventory and SC instability. Therefore, an integrated chain whose costs are managed as a whole, should favor a higher risk taking strategy across the chain, whereby some backlogs are not necessarily detrimental to the goal of SC stability and overall cost minimization. However, a chain entirely made up of low risk averse echelons could not be able to guarantee a high service level to the final customer. This drawback could be mitigated by placing a high risk averse manager at the echelon closest to the end customer (*i.e.*, the retailer). The rationale behind this composition of the chain is that the high risk averse retailer, by keeping high inventory, is able to always satisfy customer demand, while at the same time absorbing the variability of external demand itself. This makes the farthest downstream echelon a sort of buffer that allows the upper echelons to work with lower inventory and generate lower instability. To see things from a different perspective, if the focal firm in the integrated distribution chain is the retailer, the retailer with a strategic focus on customer satisfaction could reduce and control the instability of the chain by selecting suppliers characterized by lower risk aversion.

Overall, results from both the HE and MAS methodologies suggest the benefits of a moderately risky strategy across the chain, according to which “success” requires risk propensity. Our study suggests that, within a SC, excessive risk aversion is unlikely to avoid detrimental time varying phenomena such as the bullwhip effect.

Conclusions, limitations and future research

This study has presented an exploratory research on the impact of individual risk aversion on the dynamics of SCs. Although the hypothesis of risk aversion has already been incorporated in some inventory management models, there is currently a lack of models investigating risk aversion in dynamic multi-echelon settings in which the inventory decision is subject to multiple feedbacks and loops. In order to derive a working hypothesis on the impact of risk aversion on the inventory policy, we started by performing a HE with purchasing professionals recruited in the course of an international business meeting Results show that individual risk attitude leads to higher average inventory holdings. This suggests that risk aversion may be positively correlated to the desired stock and therefore with the SSF, also known as z-score.

On the base of this empirical observation, in this work we assumed that, in real life SCs, risk aversion may take place by tuning the parameters of the order policy and, in particular, the SSF. We assumed that a higher SSF reproduce a high risk aversion. Analogously, a low SSF can be associated with a low risk aversion. Thus, we explored how the orders placed by SC partners characterised by different RAs may affect the dynamics and the entire SC performance. To fulfil the research objective we model several SCs via MAS approach (SCOPE), and test the effect of several combinations of high and low risk aversion of SC partners. We measured the performance of SC in terms of operational efficiency and customer service level through a set of metrics devoted to capture dynamics of SCs. The main results suggest that:

- As the number of highly risk averse partners increases, the performance of the whole SC linearly worsens.
- SCs with the same number of highly (or low) risk averse partners present similar performances, regardless of which echelon is high (or low) risk averse.
- SCs with highly risk averse retailers provide high customer service level, regardless of the risk aversion of other echelons.

We highlight that, consistent with research such as Chandrasekaran et al. (2016), the above contributions would not have been possible without adopting a multi-method approach. While the HE uncovered the link between risk aversion and inventory holdings, and suggested the link between risk aversion and SSF, the MAS model threw light on the impact of different risk aversion attitudes on the dynamics of the multi-echelon SC.

This analysis presents some limitations that may create room for improvement and further research. First of all, although a general purpose test of risk aversion was used to assess the degree of risk aversion in the HE, risk attitudes may depend on the decision context. Therefore, future HEs should assess the sensitivity of the relation between risk aversion and inventory to the psychometric tool adopted. An important limitation is related to the modelling assumption of risk aversion. Despite the empirical and theoretical evidence has shown the relation between risk aversion, order patterns and inventory levels, we consider that other variables of an inventory control policy may be influenced by risk aversion (e.g. forecast factor, the proportional controller, etc.). Secondly, we focused on two ranges of SSF. However, other intervals may be considered. Also, It would be interesting to determine which part of the demand amplification phenomenon is due to behavioural causes, and which part is structural. In this fashion, other methodologies need to be adopted (*i.e.*, analytical methods). Finally, we do not focus on the dynamic of backlogs at higher levels of the SC. This observation may provide further insights on the potential penalties costs suffered by partners.

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